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## CALIBRATION OF A CREDIT RATING SCALE FOR POLISH COMPANIES

Increasing number of bankruptcy announcements means that even greater attention is being paid to the correct evaluation of the probability of default (*PD*) and decisions made on the basis of it. Reliable estimation of the likelihood of a company's bankruptcy reduces risk, not only for the company itself but also for all co-operating companies and financial institutions. The financial crisis has led to a tightening up of the conditions for gaining finance from banks. However, it is not only the evaluation of *PD* itself that is so important but also the correct classification of companies according to their *PD* level ("good" or "bad" companies). There is very little consideration about possible adjustments of the credit risk scale, as usually the American scale is adopted with no changes which seems incorrect. This paper stresses the importance of correct calibration of the credit rating scale. It should not be assumed (as it was in the past) that once a scale is defined it remains fixed and independent of the country. Therefore, the research carried out on Polish companies shows that the credit rating scale should be changed and the default point (i.e. "cut-off" point) should be higher than in the past. The author uses a modified classification matrix based on the probability of default. The paper compares the classification of quoted Polish companies according to their credit risk level (*PD*) with the actual occurrence of default when various default "cut-off" points are used.

Key words: *credit risk, estimation of credit risk, probability of default*

### 1. Introduction

One of the most important types of financial risk is credit risk. This risk can be defined as the *possibility of loss arising from the failure of a counterparty to make a contractual payment* [10]. Reliable estimation of the level of credit risk and the appropriate credit rating that follows reduces the threat of bankruptcy, not only of a par-

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particular company but also of all cooperating companies and financial institutions. The increasing number of bankruptcy announcements means that even greater attention is being paid to appropriate evaluation of the probability of default (*PD*). The financial crisis has led to a tightening up of the conditions for gaining finance from banks. A lot of research is being done into various models of credit risk (default models) that can be classified into different groups, e.g. structural models [2, 9, 14] or reduced form [6, 11], and their numerous modifications [3–5]. There is also research on particular elements of these models and their empirical results e.g. return rates or credit spreads [1, 7].

However, still hardly any research (e.g. [12]) has been dedicated to the field of appropriate calibration of the credit rating scale which is a real problem. Therefore, this paper stresses the importance of correct calibration of the credit rating scale.

## 2. Sources and methodology

An attempt was made to calibrate a credit rating scale which indicates whether a company has financial problems and reliably attributes a credit rating to a firm in the Polish economy. The research was based on financial data from the balance sheets of companies quoted on the Warsaw Stock Exchange (WSE) in 1999/2000–2009 and their stock prices. It should be noted that 1999 year is included in the analysis indirectly, since in order to carry out the analysis one needs the prices of the companies' stocks one year preceding the actual research. Therefore, in the results presented 2000 is regarded as the initial year. The research period covers both bear and bull markets, as well as a world-wide economic crisis which started in the USA. The choice of such a period is due to the fact that the post-war history of the Polish Stock Exchange is relatively short (it opened in 1991 with only 9 companies quoted; for example, in the following years 1992, 1993 this number was accordingly 16 and 22) and the number of companies exceeded 200 for the first time in 1999. It was not divided into further time sub-samples because, in the author's opinion, such a division could be misleading\*.

One must also take into consideration that to be included in the following analysis the companies must have been quoted for the whole period covered by the research. This condition is necessary, since to measure a company's credit risk (*PD*) one needs its stock prices. From the initially considered period of 1999–2011, two years, i.e. 2010 and 2011 were rejected due to the small number of companies fulfilling the

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\* Dividing the full sample into two sub-samples each covering five years, would create a situation in which the first period would be characterised mostly by economic growth, while the other would include growth and recession, as well as the world-wide crisis. Shorter time sub-samples seem insufficient.

above condition of continuity (this mostly covers defaulting companies, which were heavily struck by the economic crisis).

The research covered 50 companies. These companies were all registered and based in Poland and at the same time quoted on the WSE within the WIG index. These conditions ensure that these companies are good representatives of Polish companies (especially as they had to fulfil many conditions to get listed).

The paper compares the classification of quoted Polish companies according to the level of their credit risk (measured by *PD*) and the fact of whether default actually occurred using various default “cut-off” points. A classification matrix based on the probability of default was used. The main research consists of examining which threshold level of *PD* best classifies the companies according to their credit risk. The factor of interest was the fact of whether a company actually survived or not. The companies that survived are called “good” companies and those that went bankrupt – “bad” firms. It is assumed that a company is “bad” (defaulting, bankrupt) if its management or any counterparty (debtor’s petition) petitioned for insolvency or arbitrage (henceforth referred to as an “event”). It is assumed that a company is “good” if no such application was made to the court in the whole research period. “Good” companies were chosen from the same sector and branch as “bad” companies (forming pairs) and were of a similar size (measured by the value of their assets)\*. The division into “good” and “bad” companies was invariable throughout the research. However, the matrix classification changed according to a company’s *PD* level and the predetermined “cut-off” point. This is due to the fact that the assumed “cut-off” point was lowered each time by 1 p.p. The initial “cut-off” point was initially set at  $PD = 20\%$ . That is the moment when a company’s credit rating code changes from C to D, which means that the company is insolvent (see Table 1). The credit ratings of leading credit rating agencies, e.g. Moody’s Investor Company or S & P, use such a scale. The main aim of this research was to demonstrate that this level, which seems appropriate in the American economy, is not appropriate in Polish economic reality.

The estimated probability of default of the companies considered was calculated on the basis of Moody’s KMV model (henceforth referred to as MKMV). The MKMV model is based on asset volatility. The Black–Scholes–Merton model for pricing options enables estimation of the value of equity and debt. This is important because when a company is liquidated, a bondholder receives a return when the value of equity is higher than 0, which means the company’s value (*A*) is greater than its liabilities (*D*). Otherwise, a creditor does not get any return, because the market value of equity

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\*The number of “good” companies in the sample was determined by the number of “bad” companies. It was decided that the group of “good” companies is of the same number as the other group. Creating a sample which consists mostly of “good” companies seems inappropriate in relation to the aim of the research.

is 0 and the company should be announced bankrupt. This means that a creditor's return is similar to the income of a call option writer on the assets of a company taking out a loan [15, 16].

Assuming that changes in the value of assets can be described by standard geometric Brownian motion, one can calculate the probability of default ( $PD$ ) for any debtor. This is the probability that the value of the assets of a company will drop below the critical value ( $A_{\text{def}}$ ) within a given time horizon\* ( $T$ ), given by the equation:

$$PD = P \left[ \varepsilon \leq - \frac{\ln \left( \frac{A_0}{A_{\text{def}}} \right) + \left( \mu - \frac{\sigma_A^2}{2} \right) T}{\sigma_A \sqrt{T}} \right] \quad (1)$$

where:  $A$  – value of company's assets,  $A_{\text{def}}$  – critical value of a company's assets below which the company cannot pay back its debts (according to the author's model  $A_{\text{def}}$  is given by (short-term liabilities + 0.5 long-term liabilities),  $T$  – credit period,  $r$  – risk-free interest rate,  $\sigma_A$  – volatility of the value of a company's assets,  $\mu$  – average return rate on a company's assets.

In Equation (2),  $A_{\text{def}}$ ,  $D$ ,  $T$ ,  $r$  and  $\mu$  are directly observable. The market value of a company's assets ( $A$ ) and its volatility ( $\sigma_A$ ) are not directly observable and they must be estimated. To calculate these estimates, one can use the following relationship [8]:

$$E = AN(d_1) - De^{-rT}N(d_2) \quad (2)$$

$$\sigma_E E = N(d_1)\sigma_A A \quad (3)$$

where:  $d_1 = \frac{\ln \left( \frac{A}{D} \right) + (r + 0,5\sigma_A^2)T}{\sigma_A \sqrt{T}}$ ,  $d_2 = \frac{\ln \left( \frac{A}{D} \right) + (r - 0,5\sigma_A^2)T}{\sigma_A \sqrt{T}}$ ,  $E$  – company's mar-

ket equity value,  $D$  – nominal value of debt,  $\sigma_E$  – volatility of equity,  $N(d_i)$  – normal cumulative distribution function for argument  $d_i$ , where  $i = 1, 2$ .

Using Equations (2) and (3), one can calculate  $A$  and  $\sigma_A$  iteratively. They show that when a debt increases, then the debt ratio increases as well and the volatility of the value of a company's assets decreases. The growth of the debt ratio will make the probability of default ( $PD$ ) increase. Moreover, the volatility of the market value of a company's assets will negatively influence it.

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\* $PD$  is most commonly estimated with a horizon of one year [13].

The risk-free interest rate was derived from the profitability of 52-week Treasury bonds. The data on the companies came from the financial statements of quoted companies, which by law must be published each quarter. However, the companies whose standing is deteriorating often publish their financial reports with a big delay (such delays were not taken into consideration in the research) or they cease publishing them at all. Therefore, gaining full financial data on defaulting companies is usually very difficult, or, in some cases, impossible. In the research carried out, only those companies for which full reports were obtained were taken into consideration. This limits the number of defaulting companies in the research. The credit risk scales that various credit rating agencies use are very similar and assume that the company is regarded to be defaulting when its *PD* is greater than 20%. The credit risk codes and *PD* estimates are shown in table 1.

Table 1. Credit risk codes used by Moody's KMV and S & P and the corresponding *PD* levels

MKMV	S & P	<i>PD</i> [%]
Aaa	AAA	0.02
Aa	AA	0.03
A	A	0.07
Baa	BBB	0.18
Ba	BB	0.7
B	B	2.0
Caa	CCC	14.0
Ca	CC	17.0
C	C	20.0
D	D	> 20.0

Source: Moody's Investors and Standard & Poor's Agencies.

However, this scale is very inflexible, as it does not consider possible differences in the scale due to, e.g. country, region or industry. Also, other thresholds may change (increase or decrease). It is also important to note that this scale should also vary in times of recession for it cannot be assumed that the scale then reflects the situation of a company in the same way as during a period of prosperity.

### 3. Research and results

The first step in the research was to divide companies into two groups: "good" and "bad" firms, according to whether they had petitioned for insolvency or arbitrage.

A list of these companies with their classification into “good” or “bad” is shown in Table 2 (the date in parentheses next to a “bad” company’s name indicates the time of petitioning).

Table 2. List of companies considered with the division into “good” and “bad” firms

No.	“Bad” companies	Occurrence <sup>a</sup>	No.	“Good” companies
1	Apexim S.A.	(1) 2002-09-27	1	Ambra S.A.
2	Beef-San S.A.	(3) 2002-07-23	2	Amica Wronki S.A.
3	Bick S.A.	(1) 2005-07-18	3	Atlanta S.A.
4	Elektromontaż-Export S.A.	(3) 2002-12-24	4	Bakalland S.A.
5	Energoaparatura S.A.	(1) 2004-08-26	5	Budimex S.A.
6	ESPEBEPE S.A.	(2) 2002-05-13	6	Efekt S.A.
7	Ferrum S.A.	(3) 2003-12-23	7	Elkop S.A.
8	GKI S.A.	(2) 2002-07-15	8	Elstar Oils S.A.
9	Howell S.A.	(3) 2002-10-04	9	Energomontaż-Południe S.A.
10	Krosno S.A.	(2) 2009-03-17	10	Energomontaż-Północ S.A.
11	Mitex S.A.	(3) 2004	11	Farmacol S.A.
12	Mostostal Gdańsk S.A.	(1) 2003	12	Globe Trade Centre S.A.
13	Mostostal-Export S.A.	(1) 2002	13	Graal S.A.
14	Naftobudowa S.A.	(3) 2002-03	14	Indykpol S.A.
15	Odlewnie S.A.	(3) 2009-01-16	15	Jutrzenka S.A.
16	Pekabex S.A.	(3) 2003	16	Kruszwica S.A.
17	Piasecki S.A.	(1) 2002-07-31	17	Mieszko S.A.
18	PKM Duda S.A.	(1) 2009-03-24	18	PBG S.A.
19	Polnord S.A.	(3) 2005	19	Pemug S.A.
20	Pozmeat S.A.	(1) 2003-03-11	20	PEPEES S.A.
21	PPWK S.A.	(3) 2002-11-28	21	PGF S.A.
22	Rafamet	(1) 2002-02-12	22	Prochem S.A.
23	Resbud S.A.	(3) 2001	23	Rafako S.A.
24	Swarzędz S.A.	(3) 2009-03-20	24	Wawel S.A.
25	Tonsil S.A.	(3) 2001-06	25	Wilbo S.A.

<sup>a</sup>(1) petitioning for insolvency, (2) insolvency, (3) petitioning for arbitrage.

Source: Author’s work.

In the case that petitioning for insolvency occurred before the period of analysis (before 2000), then the fact of an actual default was taken as an indicator of a “bad” company (such instances in the analysis appeared in the case of 3 companies).

The next step was to calculate the *PD* of all the companies. The *PD* of “good” companies was taken to be the average over the period analyzed. The *PD* of “bad” companies was calculated in two ways, by averaging over 1 or 2 years before the event of petitioning (averaging over 1/2 year before the event was also considered, but the results obtained in this way were identical to those using a period of one year, so

they are not presented). The *PD* calculated in such a way can be regarded as the “*PD* conditional” on the occurrence of the event. In such a case, the conditional *PD* measure minimizes the probability of a type II error which concerns the companies which defaulted before they reached the threshold level. One can say that this neglects the probability of a type I error involving the companies which reached the threshold without eventually defaulting. However, from the point of view of financial institutions (e.g. banks), it is crucial to avoid granting finance to companies which will not be able to return the debt due to insolvency. In this case, optimisation involves the avoidance of potential losses, which also includes refusing funding to those companies which reached the threshold, but did not eventually default. This kind of optimisation can be called “loss minimising”.

Table 3. Classification matrix with a changeable “cut-off” point (15–20%) and one-year averaging

Contribution		“Bad” companies	“Good” companies
<i>PD</i> > 20%	No. of firms	10	0
<i>PD</i> ≤ 20%		15	25
<i>PD</i> > 20%	percentage	40%	0%
<i>PD</i> ≤ 20%		60%	100%
<i>PD</i> > 19%	No. of firms	16	0
<i>PD</i> ≤ 19%		9	25
<i>PD</i> > 19%	percentage	64%	0%
<i>PD</i> ≤ 19%		36%	100%
<i>PD</i> > 18%	No. of firms	21	1
<i>PD</i> ≤ 18%		4	24
<i>PD</i> > 18%	percentage	84%	4%
<i>PD</i> ≤ 18%		16%	96%
<i>PD</i> > 17%	No. of firms	<b>23</b>	<b>2</b>
<i>PD</i> ≤ 17%		<b>2</b>	<b>23</b>
<i>PD</i> > 17%	percentage	<b>92%</b>	8%
<i>PD</i> ≤ 17%		8%	<b>92%</b>
<i>PD</i> > 16%	No. of firms	24	4
<i>PD</i> ≤ 16%		1	21
<i>PD</i> > 16%	percentage	96%	16%
<i>PD</i> ≤ 16%		4%	84%
<i>PD</i> > 15%	No. of firms	25	6
<i>PD</i> ≤ 15%		0	19
<i>PD</i> > 15%	percentage	100%	24%
<i>PD</i> ≤ 15%		0%	76%

Source: author’s calculations

After that, twelve classification matrices were constructed: six for an averaging period of one year before the time of default (see Table 3) and the other six for an

averaging period of 2 years (see Table 4). These two sets of six matrices were combined into two tables. In both cases, the starting “cut-off” point was set at  $PD = 20\%$  and then successively lowered by 1%.

Table 4. Classification matrix with a changeable “cut-off” point (15–20%) and two-year averaging

Contribution		“Bad” companies	“Good” companies
$PD > 20\%$	No. of firms	9	0
$PD \leq 20\%$		16	25
$PD > 20\%$	percentage	36%	0%
$PD \leq 20\%$		64%	100%
$PD > 19\%$	No. of firms	14	0
$PD \leq 19\%$		11	25
$PD > 19\%$	percentage	56%	0%
$PD \leq 19\%$		44%	100%
$PD > 18\%$	No. of firms	17	0
$PD \leq 18\%$		8	25
$PD > 18\%$	percentage	68%	0%
$PD \leq 18\%$		32%	100%
$PD > 17\%$	No. of firms	22	1
$PD \leq 17\%$		3	24
$PD > 17\%$	percentage	88%	4%
$PD \leq 17\%$		12%	96%
$PD > 16\%$	No. of firms	<b>23</b>	<b>1</b>
$PD \leq 16\%$		<b>2</b>	<b>24</b>
$PD > 16\%$	percentage	<b>92%</b>	4%
$PD \leq 16\%$		8%	<b>96%</b>
$PD > 15\%$	No. of firms	25	3
$PD \leq 15\%$		0	22
$PD > 15\%$	percentage	100%	12%
$PD \leq 15\%$		0%	88%

Source: author’s calculation.

The research showed that one should not blindly set the “cut-off” point at a level of  $PD = 20\%$ , as generally it can lead to incorrect results and subsequent wrong decisions. The research shows that increasing the “cut-off” point does not improve the results. As one can notice, the percentage of “bad” companies correctly classified as defaulting is decreasing in the “cut-off” point. When  $PD = 20\%$ , only 40% of all “bad” companies are classified in the right group. This proves that defaulting companies can have a smaller  $PD$  and go bankrupt within just one year. The trend of improving the results follows until the cut off point is  $PD = 15\%$  (the research also covered cut off points less than 15%, but this proved pointless as lowering the cut off point



only deteriorated the classification of “good” companies at a 100% efficient classification of “bad” companies, so it is not presented).

It may be assumed that the most reliable “cut-off” point is  $PD = 17\%$ . This level is beneficial, as well as meaningful, for at least two reasons. Firstly, as one can notice it enables correct classification of both “bad” and “good” companies at a reasonable level higher than 90% (see Table 3;  $PD = 17\%$ ). In this case, exactly 92% of firms in both groups are correctly classified. It must be remembered that when it comes to assessing credit risk, it is not only important to classify “bad” companies correctly (although one can make this a priority) but also to correctly classify the other group – “good” companies. In times of economic crises, banks (financial institutions) first and foremost need to minimise their losses by limiting the probability of default of the companies that they finance. Of course, on the other hand, they would also want to optimise the profit which comes from financing “good” companies and lowering the number of “good” companies by classifying too many of them into the group of “bad” firms will result in decreasing their income. The second reason is that at  $PD = 17\%$  the credit rating changes from CC to C, which makes it simple to assume that in the Polish economy not only the companies that obtain a rating D, but also those rated C should be recognised as bankrupt. Therefore, the best choice of a “cut-off” point is  $PD = 17\%$ . In the case of averaging  $PD$  for a two-year period before announcing default, the situation is similar, however, not exactly the same. The detailed results are presented in Table 4.

One can observe that in the case of averaging over a two-year-period the best choice for the “cut-off” point is  $PD = 16\%$ . This ensures correct classification of firms in both groups at a level higher than 90% (accordingly 92% for “bad” companies and 96% for “good” ones). At  $PD = 17\%$ , the correct classification rate is close to 90% for “bad” companies (precisely 88%) and still 96% for “good” firms. This leads to the conclusion that when doing the analysis before decision making, the “cut-off” point should be set at  $PD = 17\%$  (due to the fact that  $PD$  analysis is usually carried out for a period of one year). When the analysis covers a two-year-period it could be even lowered to  $PD = 16\%$ . On the other hand, it is economically correct that during two years the standing of company can change radically, so such analysis bears more risk. Hence, one should be very conscious about rejecting prospective “good” companies as described above.

## 4. Conclusions

The main aim of this research was to demonstrate that an inflexible “cut-off” point of 20%  $PD$  (for discriminating between “good” and “bad” companies defined above)

does not work well in the Polish economy. This is because it cannot be assumed (as it was in the past) that once stated scale is invariable and independent of the country. Therefore, the research carried out on Polish companies shows that the credit rating scale should be changed and the default point should be lower than in the past. In the case of Polish companies, it should be at the level of 17% for a one-year analysis and 16% for a two-year analysis, instead of the generally assumed 20%. Decreasing the cut off point improves the classification of “bad” firms accordingly from 40% (1 year) and 36% (2 years) to 92% in both cases. Further lowering of the “cut-off” point seems pointless. Although it improves the classification of “bad” companies” to 100%, it also radically deteriorates the classification of “good” companies. Therefore, a sensible compromise can be achieved at  $PD = 17\%$  (16%). Further research should be carried out for individual branches, because the “cut off” point could also vary across different industries.

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