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MACROECONOMIC FACTORS IN MODELLING THE SMES BANKRUPTCY RISK. THE CASE OF THE POLISH MARKET

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Abstract: The last financial crisis affected the SMEs sector in different countries at different levels and strength. SMEs represent the backbone of the economy of every country. Therefore, they need bankruptcy prediction models easily adaptable to their characteristics. In our analysis we verified hypothesis: including information about macroeconomic conditions significantly increases the effectiveness of the bankruptcy model. The data set used in our research contained information about 1,138 SMEs. All information was taken from the financial statements covering the period 2002-2010. The sample included enterprises from sectors: industry, trade and services. Selected financial ratios were used to build the model and the macroeconomic variables were added: GDP, inflation, and the unemployment rate. Logistic regression as the research method was applied. In our study we showed that the incorporation of the macro variables improved the prediction of the SMEs bankruptcy risk.

Keywords: bankruptcy risk model; logistic regression; macro variables.

1. Introduction

In Poland the economic situation during the last financial crisis and after it was quite stable in comparison to other European countries. The last financial crisis affected the SMEs sector in different countries at different levels and strength. Even in the EU, some economies suffered less compared to others. SMEs represent the backbone of the economy of every country. Therefore, they need a prediction model easily adaptable to their characteristics. Poland was a leader of growth among all OECD countries [Raport o stanie… 2012]. Faster than ever, the distance to Western

European countries decreased. The country still retained its high financial credibility, avoided the recession, dramatic currency crises and debt crises. Those phenomena deeply affected other European countries including our Central and East-European neighbours. One of the pillars of this success were effectively operating Polish companies. Corporationes were able to flexibly adjust their operations to the crisis environment. The adjustment abilities of small companies were obvious but their expectations about the end of the recession were more apparent.

This behaviour is not the most effective from a company's point of view but is a visible sign of the Polish transformation's success. Polish companies are doing as well as their highly capitalized foreign competitors. They have a past history full of harsh conditions of survival and now they are more resistant to crises. SMEs are flexible and adjustable (due to the low employment and expenditure limitations) to changing economic conditions. Resilience to crises depends also on their low levels of exports. SMEs do not use external funding and are more conservative towards expansion, and in consequence are not involved in risky financial operations and big investment projects. The majority of Polish SMEs are involved in the service sector which suffer least from the crises. SMEs react to crises by decreasing employment Orłowski et al. [2010].

In our analysis the following hypothesis was tested: incorporating information about the macroeconomic conditions of a company's operation significantly increases the effectiveness of the model that forecasts a company's bankruptcy.

2. Literature review

The literature on bankruptcy risk modelling is extensive, and started 50 years ago when Altman [1968] proposed his Z-score model for predicting the probability of default of companies. From that time onwards, different modelling approaches have been developed and applied. One of them is the usage of the macroeconomic variables in the default model [Thomas, Stepanova 2002; Carling et al. 2002; Bellotti, Crook 2007; Agrawal, Maheshwari 2014]. Recent papers have looked at modelling the credit risk using the macro variables. Carling et al. [2002] suggested that the capital requirement based on the IRB approach can vary significantly depending on the phase of the business cycle. In a recession it can exceed the capital adequacy requirement, while in times of prosperity it can fall to low levels. Koopman and Lucas [2005] analysed the default rate of U.S. firms and found that GDP growth is significant.

Jakubik [2006] applied Merton structural models to the Czech economy. His model confirmed the very strong link between bank portfolio quality and the macroeconomic environment.

Simons and Rolwes [2009] also considered the application of the macroeconomic-based model for estimating probabilities of default. They looked at the relation between macroeconomic variables such as GDP growth, interest rates, exchange rates, stock market returns and volatility, and oil prices, and the default behaviour of Dutch firms. Authors found a negative relation with the default rate and GDP growth, and the relation with the oil price turned out to be significant in several sectors. For other macro variables, namely the interest rate, exchange rate, and oil price, the level of the variables was relevant to the default rate.

The application of the macro variables was carried out by Agrawal et al. [2014]. The authors found the significant macroeconomic variables, incorporated as sensitivity variables that affect the financial distress of the Indian companies. In this study they used two alternative statistical techniques, namely logistic regression and multiple discriminant analysis. According to the results, stock market sensitivity and sensitivity to changes in inflation and the Consumer Price Index (CPI) sensitivity, have a significant impact on the default probability of companies. More precisely, stock market sensitivity has a significant positive impact where CPI sensitivity has a significant negative relationship with the probability of default.

Malik and Thomas [2012] proposed a Markov chain model based on behavioural scores and included economic variables as well as the age of the loan. The research highlights the fact that behavioural scores are dynamic which depends on changes in the economic conditions. The authors suggest that in more volatile conditions, or when using the model for stress testing, it would be important to include the economic effects in the modelling.

Figlewski et al. [2012], analysed firm-specific covariates related to a firm's credit rating history and a wide range of the macroeconomic variables in a Cox model. They observed that aggregate default rates also vary substantially over time, presumably reflecting changes in the general economic conditions. More precisely, the intensities of the occurrence of credit events are significantly affected by macroeconomic factors.

All the above findings inspired the authors to use the macroeconomic variables for the model based on the Polish SMEs. For this purpose first a model was built based only on the financial factors without macro variables, and then the results were compared after applying the macro variables. For the second model GDP, inflation, and the unemployment rate were used. The results were analysed and compared, showing that the application of these variables improves model prediction and affects SMEs' probability of default.

3. Data and methods

The data set used in our research contains information about 1,138 SMEs operating on the Polish market. All the information comes from the companies' financial statements covering the period from 2002 to 2010. Note that the whole economic cycle was included.

The data set was balanced in such a way that the number of bankrupted and non-bankrupted companies is equal to 569. For modelling and validation purposes the data set was divided in the proportion of 60:40. The sample contains enterprises from different segments, namely: industry, trade and services.

The method applied to the data was logistic regression. The general form of logistic regression:

$$Y \sim B(1, p),$$
$$p = E(Y|X) = \frac{\exp(\boldsymbol{\beta}\mathbf{X})}{1+\exp(\boldsymbol{\beta}\mathbf{X})},$$

where: $B(1, p)$ it is a binomial distribution with probability of success p; Y – dependent variable; $\mathbf{X} = [X_1,\ldots,X_k]$ – explanatory (independent) variables; $\boldsymbol{\beta}$ – coefficients.

The cut-off point is an important element in the logistic regression model. The estimation based on a balanced sample usually takes 0.5 as the cut-off value. The structure of the sample (the percentage of bankrupted enterprises) determines the cut-off value.

The interpretation of the results is usually based on the odds ratios (the ratio of odds in two groups or in change of one unit in the explanatory variable). Logistic regression requires a number of different assumptions to be fulfilled. The most important assumptions are: randomness of the sample, a big sample, no collinearities in explanatory variables, and independence of observation.

The choice of the financial ratios used to build the model was based on Pociecha [Pociecha et al. 2014], Bellovary et al. [2007], Jagiełło [2013]. In the next step the macroeconomic variables were added, namely GDP, inflation, and the unemployment rate.

Table 1 presents the final set of the ratios used in the initial analysis.

Two logistic regression models were built:

- a logistic regression model based only on the selected financial ratios.
- a logistic regression model with financial and macroeconomic variables (GDP, inflation, and the unemployment rate).

The selection of the variables to the model was based on the clustering method. In order to choose the ratios, the grouping variables procedure was used.

Clusters of variables in this algorithm can be treated as linear combinations of those variables in the cluster. Each linear combination of those variables is the first principal component of the cluster. Just like in Principal Component Analysis (PCA) the first principal component is the weighted average of the variables with estimated weights to explain as much as possible of the variation. As a contradiction to PCA in this method the principal components can be correlated. In PCA, successive components are calculated based on the same set of variables. In the Variables Clustering method the authors consider only the first principal components, but each of them is calculated based on a different set of variables. The variables clustering algorithm is searching for such a division of variables that maximizes the variation explained by the components of the clusters summed up by all the clusters.

Table 1. Financial ratios used in the initial analysis

Ratio	Name	Formula
w1	current liquidity	$\frac{current\ assets}{short-term\ liabilities}$
w2	quick ratio	$\frac{current\ assets-inventory-prepayments}{short\ term\ liabilities}$
w3	liquidity cash	$\frac{cash}{short-term\ liabilities}$
w4	capital share in assets	$\frac{current\ assets-short\ term\ liabilities}{total\ assets}$
w5	gross margin	$\frac{gross\ profit\ /\ loss\ on\ sale}{operating\ expenses}$
w6	operating profitability of sales	$\frac{profit\ /\ loss\ on\ operating\ activities}{total\ revenues}$
w7	operating profitability of assets	$\frac{profit\ /\ loss\ on\ operating\ activities}{total\ assets}$
w8	net profitability of equity	$\frac{net\ profit\ /\ loss}{equity}$
w9	assets turnover	$\frac{total\ revenues}{total\ assets}$
w10	current assets turnover	$\frac{total\ revenues}{current\ assets}$
w11	receivables turnover	$\frac{total\ revenues}{receivables}$
w12	inventory turnover	$\frac{total\ revenues}{inventory}$
w13	capital ratio	$\frac{equity}{total\ liabilities}$
w14	coverage of short-term liabilities by equity	$\frac{equity}{short-term\ liabilities}$
w15	coverage of fixed assets by equity	$\frac{equity}{fixed\ assets}$
w16	share of net financial surplus in total liabilities	$\frac{net\ profit\ /\ loss+\ amortisation+\ interests}{total\ liabilities}$

Source: own elaboration.

The variables with the smallest value of the parameter below are selected as the best variables in the clusters:

$$\left(1-R^2\right)\text{Ratio}=\frac{1-R_G^2}{1-R_I^2},$$

where: R_G^2 is R^2 of the variable with the principal component in the cluster; R_I^2 is R^2 of the variable with the principal component of the nearest cluster.

The variable with the smallest value of the $(1 - R^2)$Ratio is highly correlated with its cluster components and weakly correlated with the components of other clusters. That is why this variable is selected as representative of this cluster. This feature assures the noncollinearity between the explanatory variables. This procedure applied principal components, obtaining six clusters and representatives of those clusters (see: Figure 1).

Cluster 1: **W2**, W14, W15, W16, W1
Cluster 2: **W4**, W13, W7
Cluster 3: **W10**, W11, W9
Cluster 4: **W6**, W5
Cluster 5: **W12**
Cluster 6: **W8**

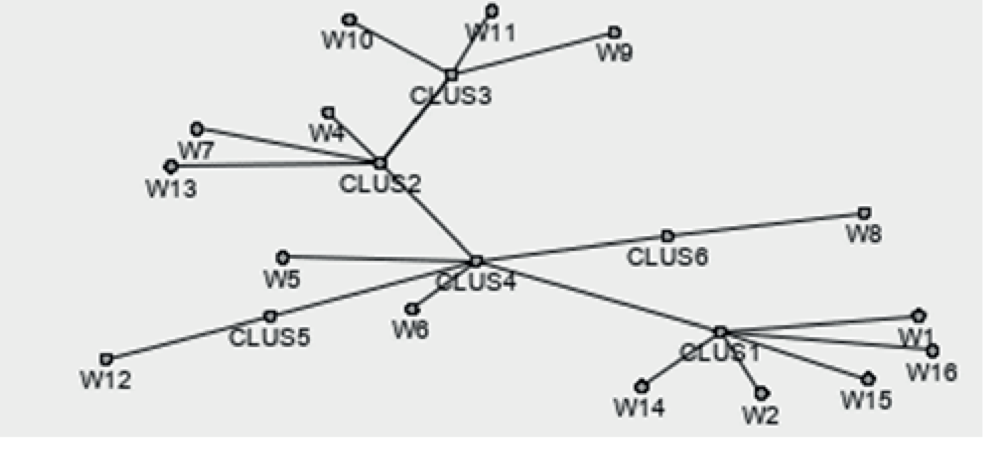

Fig. 1. Grouping variables procedure – the results

Source: own elaboration.

3.1. Logistic regression model based only on the selected financial ratios

As the basis, the logistic regression model with only financial ratios was estimated. Only two variables were significant at the 0.05 significance level: current assets turnover and capital share in assets (see Table 2). Higher values of those ratios decreases the risk of bankruptcy.

Table 2. Logistic regression with only financial ratios – results

Parameter	Estimate	Std. error	Chi-sq Wald	*p*-value	Odds ratio
Intercept	0.3128	0.1378	5.15	0.0233	
W10 current assets turnover	−0.0722	0.0272	7.05	0.0079	0.930
W12 inventory turnover	−3.26E−6	7.767E−6	0.18	0.6751	1.000
W2 quick ratio	−0.00003	0.00318	0.00	0.9934	1.000
W4 capital share in assets	−2.0232	0.3106	42.43	<.0001	0.132
W6 operating profitability of sales	−1.79E−6	0.000049	0.00	0.9711	1.000
W8 net profitability of equity	0.00528	0.00968	0.30	0.5854	1.005

Source: own elaboration.

3.2. Logistic regression model with macroeconomic variables: GDP, inflation, and the unemployment rate

In the second model (with the financial ratios and macroeconomic variables) except for the two financial ratios, two macroeconomic variables were also significant, namely the unemployment rate and GDP. Higher GDP and a higher unemployment rate decreases the risk of bankruptcy. These results confirm other research findings such as those of Koopman and Lucas (2005), and Simon and Rolwes [2009].

Table 3. Logistic regression with financial ratios and macroeconomic variables – the results

Parameter	Estimate	Std. error	Chi-sq Wald	*p*-value	Odds ratio
Intercept	2.3157	0.9409	6.06	0.0138	
Unemployment	**−0.1551**	**0.0423**	**13.47**	**0.0002**	**0.856**
Inflation	0.1462	0.1096	1.78	0.1824	1.157
GDP	**−0.1162**	**0.0505**	**5.30**	**0.0213**	**0.890**
W10 current assets turnover	**−0.0714**	**0.0270**	**6.99**	**0.0082**	**0.931**
W12 inventory turnover	−3.09E−6	0.000010	0.09	0.7687	1.000
W2 quick ratio	−0.00003	0.00225	0.00	0.9909	1.000
W4 capital share in assets	**−2.1935**	**0.3310**	**43.92**	**<.0001**	**0.112**
W6 operating profitability of sales	−1.66E−6	0.000050	0.00	0.9733	1.000
W8 net profitability of equity	0.00897	0.0100	0.80	0.3713	1.009

Source: own elaboration.

3.3. Model comparison

The overall accuracy of the model with macro variables is higher compared to the model with financial ratios only. The AUC value (see ROC curves in Figure 2) is higher for the model with macroeconomic variables. However, the accuracy of bankruptcy prediction is comparable. In the case of the accuracy of non-bankrupted companies, the prediction is higher for the model with macroeconomic variables.

Table 4. Classification table for train and validation sample

Model	Data set	FN	TP	FP	TN	First type error
Logistic regression	train	138	227	114	202	33.4% (114/341)
Logistic regression with macrovariables	train	110	226	115	230	33.7% (115/341)
Logistic regression	validation	107	153	75	122	32.9% (75/228)
Logistic regression with macrovariables	validation	82	151	77	147	33.8% (77/228)

Source: own elaboration.

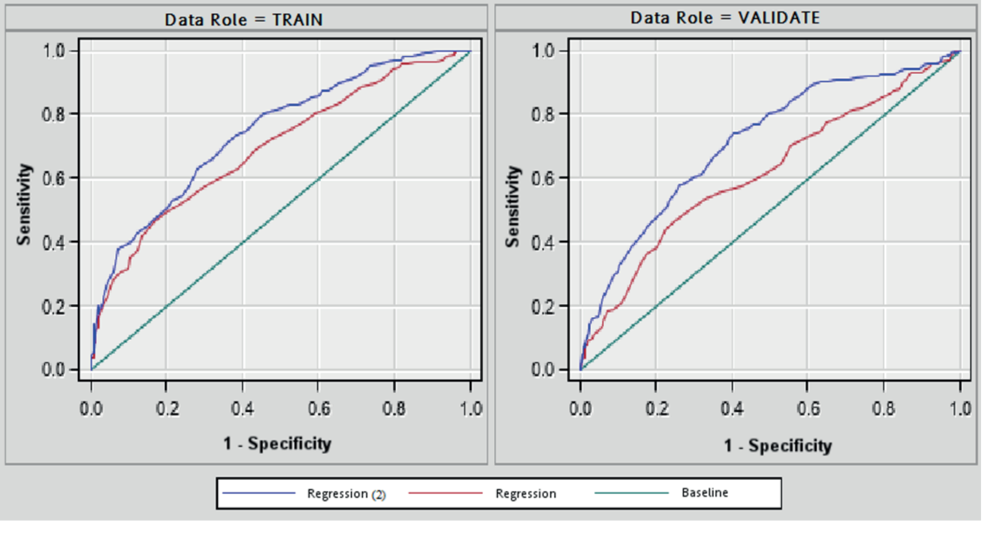

Fig. 2. ROC curves for models: train and validation sample

Source: own elaboration.

4. Conclusions

The general conclusion is that the strength of the models' classification on the small samples is rather weak.

Significant financial indicators in the model are:

- current assets turnover,
- capital share in assets.

Macroeconomic indicators important in the model are:

- GDP (dynamics),
- unemployment.

Higher GDP dynamics and a higher unemployment rate decreases the risk of bankruptcy. This relation was also confirmed by other research results [Jakubik 2006; Simons, Rolwes 2009; Agrawal et al. 2014].

Classification effectiveness was improved in the model with the macroeconomic variables, but the first type error (Table 4) achieved comparable values (33.4%, 33.7%, respectively).

The application of the macro variables in the model improves the classification, especially for the companies that are in a good condition.

In the study, the authors showed that the incorporation of the macro variables improved the prediction of the risk of SMEs default. The obtained results show that the application of the macro variables in the bankruptcy risk model improves the predictive performance. The results also confirm some earlier findings that macroeconomic conditions influence the default rate [Simons, Rolwes 2009], in particular GDP is quite significant for the estimation of the default risk [Koopman, Lucas 2005]. In practice, the proposed model with macro variables can be used to assess SMEs bankruptcy risk. In future, the authors would like to extend their research to other econometric models as well as analyse a wider range of macro variables.

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CZYNNIKI MAKROEKONOMICZNE W MODELOWANIU RYZYKA UPADŁOŚCI MŚP. PRZYKŁAD RYNKU POLSKIEGO

Streszczenie: Ostatni kryzys finansowy dotknął sektor MŚP w poszczególnych krajach w różnym stopniu i z różną siłą. MŚP stanowią podstawę gospodarki każdego kraju, dlatego potrzebne są modele predykcji upadłości tych przedsiębiorstw łatwo dostosowujące się do ich zmieniających się charakterystyk. W artykule poddano weryfikacji hipotezę: włączenie do modelu informacji o warunkach makroekonomicznych istotnie podnosi efektywność modelu przewidującego upadłość przedsiębiorstw. Zbiór danych wykorzystany w badaniu zawierał informację o 1138 MŚP. Informacja została zaczerpnięta ze sprawozdań finansowych z lat 2002-2010. Próba zawierała przedsiębiorstwa z sektorów: produkcyjnego, handlowego i usługowego. Do budowy modelu wykorzystano wybrane wskaźniki finansowe i zmienne makroekonomiczne: PKB, inflację, stopę bezrobocia. Jako metodę badawczą zastosowano regresję logistyczną. W analizie wykazano, że włączenie zmiennych makroekonomicznych poprawia jakość predykcji upadłości MŚP.

Słowa kluczowe: modele ryzyka upadłości, regresja logistyczna, zmienne makroekonomiczne.