Method for assessment of companies' credit rating (AJPES S.BON model)

Short description of the methodology

Ljubljana, May 2011

ABSTRACT

Assessing Slovenian companies' credit rating scores using the **AJPES S.BON** model is based on analyzing financial statements and occurrence of payment default events for the entire population of Slovenian companies over a longer period of time. **Payment default event** is defined as the occurrence of at least one of the following events: initiation of bankruptcy, composition, liquidation or compulsory liquidation proceedings. Transaction account blocks and court notices issued for companies and subsidiaries are considered soft information, taken into account when updating credit rating scores during the year, or after credit rating scores have been assigned based on the annual report.

Credit rating assessment complies with Basel II regulations, which corporate banks use in calculating capital requirements for credit risks. Based on financial statements and the financial indicators calculated on the basis thereof, individual risk factors for the potential occurrence of a payment default event are analyzed (profitability, liquidity, indebtedness, activity, size, productivity and growth of business) and their contribution to the total probability of the potential occurrence of a payment default event.

To ensure the specific ways in which individual companies from various industries conduct their business are considered to the highest extent, the AJPES S.BON model includes several sector-specific submodels for companies, which are applied according to their principal activity. The AJPES S.BON model is used to calculate each company's overall probability of a payment default event occurring within the next 12 months after the date of the company's financial accounts. The sample-dependent values are calibrated with consideration to the characteristics of the Slovenian economy and individual industry sectors over a longer time period, which includes the overall macroeconomic cycle. The sample-independent or calibrated payment default probabilities are the basis for determining credit rating scores using the AJPES S.BON model. The result are unbiased credit ratings for the entire population of Slovenian companies, which will help banks assess the credit risk involving the probability of a payment default event for any Slovenian company. Other entities will be able to use these credit rating scores as a basis for examining the ability of selected companies/business partners to meet their financial obligations.

The AJPES S.BON model classifies Slovenian companies into **10 credit rating categories** according to the credit risk, represented by **credit rating scores** ranging from **SB1** to **SB10**. The credit rating scores are defined on a scale of probability that at least one of the different types of payment default events will occur in a specific case in the 12-month period following the date of the relevant financial statements upon which the credit rating score is based. The first 10 credit ratings (SB1 through SB10) represent **categories of payers**, and the credit rating SB10d represents the **non-payer category**. The credit rating score of **SB10d** is assigned to companies in which a payment default event has actually occurred.

The probability of the occurrence of a potential payment default event is lowest with the credit rating of SB1, increasing exponentially as we move towards the credit rating of SB10.

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Chapter 1

1. Underlying data used in the AJPES S.BON model

1.1. Annual reports on company activities

The core database used in development of the AJPES S.BON model consists of financial statements of all active Slovenian companies, made at the end of the financial year in the 2002-2009 period. Companies submit their annual reports to AJPES in order to ensure publicity of data and for national statistics purposes. Pursuant to the Companies Act (Official Gazette of the Republic of Slovenia, issue no. 42/2006, 60/2006-amended and 10/2008, hereinafter: ZGD-1), companies are required to submit their annual reports (this includes all legal forms defined in the ZGD-1 except silent partnerships, which are not considered legal entities). This also applies to those legal entities whose individual acts stipulate that they are required to keep books of account and prepare annual reports in accordance with ZGD-1 (e.g. public commercial institutes and other legal forms which provide commercial public services).

In addition to company performance data from annual reports, AJPES S.BON model also collects information on the occurrence of payment default events for the Slovenian companies in the 2002-2009 period in order to assess the likelihood of payment default and assign a credit rating score, while accounting for the one-year gap between the financial statements and the occurrence of payment default event. The corresponding payment default events were thus collected for the period 2003-2010, on the population of companies existing in the 2002-2009 period. In order to calibrate and normalize the model, we also collected information on the incidence of payment default events by year on a longer time horizon, which includes the entire macro-economic cycle, for the period from 1994 to 2010. Thus, in our assessment of the parameters of the AJPES S.BON model, the characteristics of the Slovenian economy were considered to the largest extent possible, reflected in the incidence of payment default events.

1.2. Definition of the payment default event and collection of payment default data

Defining the occurrence of a payment default event is of crucial importance from the aspect of assessing the model and its usefulness to the end user of credit rating information, since the extent of the definition affects the realized payment default rates. The definition of payment default was expanded with the new Basel Accord (Basel II). It is deemed that a default event has occurred on the debtor's side, when either or both of the following events occur (Resolution on the Calculation of the Capital Requirement for Credit Rating Using the Internal Credit Rating Systems for Banks and Savings Institutions Approach, Official Gazette of the RS, 135/2006):

- The bank believes that there is little probability that the debtor will repay its credit obligations towards the bank, its supervising companies or any of its subordinated companies **in full**, without having to employ measures such as disposal of financial insurance - foreclosure (if any);
- A debtor is more than 90 days late on the payment of any significant credit liability towards the bank, its supervising company or any of its subordinated companies.

Notwithstanding the above definition, there are differences between countries as to the definition of payment default events which complies with the Basel II standard, and there are differences in the laws governing the bankruptcy of companies.

Bearing in mind the limitations regarding availability of direct bank data, we tried to come as close as possible to the payment default event as defined by Basel II when assessing the AJPES S.BON model. A Payment default event is therefore defined as the occurrence of one of the following events:

- ***bankruptcy of a company;***
- ***initiation of compulsory composition proceedings against a company; and***
- ***initiation of liquidation and/or mandatory liquidation of a company.***

1.2.1. Insolvency (bankruptcy, compulsory composition, liquidation)

In accordance with the Commercial Register of Slovenia Act AJPES manages the Slovenian Business Register (SBR) as the central database on all business entities based on the territory of the Republic of Slovenia and involved in a profit or non-profit business activity. As of 1.2.2008, the court register forms part of the SBR, which means that the data on companies contained in the SBR is entirely up-to-date.

The court register, as part of the SBR, has two parts: the main register and documentary archive. The main register contains information about the individual subject of the entry, as provided in the Court Register Act (this includes data on initiated bankruptcy proceedings, compulsory composition proceedings, liquidation or compulsory liquidation proceedings). The resolution on the initiation of compulsory composition, bankruptcy or liquidation proceedings is entered in the SBR, as well as the resolution on conclusion of the compulsory composition, bankruptcy or liquidation proceedings, with a brief mark of the manner in which the proceedings were concluded, and the resolution on confirmation of the compulsory composition having taken place. The manner of entry of these data is defined in further detail in the Financial Operations of Companies Act, under insolvency and compulsory liquidation proceedings. Registration courts decide on the entry of data which are required by law to be entered into the court register.

The entry in the court registry and consequently in the SBR is carried out immediately after the court decision on registration is issued and published on the AJPES website at the time of registration, which is extremely important as publicity effects come into being at the time of publication of the entry in the court register. The AJPES website also contains the underlying documents which served as a basis for registration in the court register, and documents which are filed in the documentary archives pursuant to the law.

Until 1.2.2008 data on initiated bankruptcy proceedings, compulsory composition proceedings and liquidation was entered in the SBR on the basis of decisions received, which AJPES or the entities themselves sent to competent courts. At least once per year, AJPES also carried out reconciliation of data with the court register, which further ensured that the data kept in the SBR was complete and up-to-date.

Data entered in the SBR or the court register is public. AJPES ensures data publicity by allowing access via its website (ePRS application), providing SBR printouts and preparing data packages selected according to user criteria. Easy access to data and a large user base further increases the quality of SBR data.

Chapter II

2. Main steps involved in the preparation and assessment of the AJPES S.BON model parameters

The first step defines different financial indicators which, according to economic theory, have explanatory significance for anticipating payment default events and cover various risk factors leading to the payment default event: liquidity, profitability, indebtedness, activity, productivity, size and operational growth. Their predictive power in explaining the occurrence of a payment default event is tested and analyzed. Over the course of the testing process the specifics of the operations of companies are taken into consideration depending on their relevant industry or field of operations.

In the next step these indicators, are transformed according to the best options offered by economic theory and current professional practice. In the transformation of indicators we pursue the goal of obtaining maximum predictive power of the model in explaining the occurrence of a payment default event.

The transformed indicators are then entered into multivariate sector submodels for assessment of the payment default probability, and their parameters will be assessed through application of logistic regression. Different statistic methods are used to select the optimum combination of transformed financial indicators by sectoral submodel.

The next step is testing the distinguishing ability of multivariate logistic models and calibration of payment default rates.

2.1. Financial indicators and analysis of individual risk factors

In economic theory no generally accepted theory exists which determines factors which directly affect whether companies become insolvent and how exactly this happens. When studying this phenomenon we draw on financial indicators calculated from financial statements. These are often understood as symptoms of approaching insolvency. In practice the following groups of indicators are used:

- profitability and cash flow indicators,
- indebtedness or financial leverage indicators,
- liquidity indicators,
- activity and asset management indicators,
- productivity indicators,
- growth indicators and
- size indicators.

Financial indicators present basic company performance characteristics in terms of their economic features and competitive advantages, allowing comparison between different enterprises, since the calculation method helps to eliminate the effect of the enterprise size. This applies to all the aforementioned groups of financial indicators, with the exception of enterprise size indicators which are not ratios between financial categories but are financial categories in themselves.

Companies from different industries have different operating characteristics, reflected in specific segments of their financial statements, and consequently also in the calculated financial indicators. Due to the aforementioned characteristics the financial indicators and their effect on the incidence of payment default events are analyzed separately by sectoral submodel.

In theory there are a multitude of different indicators which can be calculated from companies' financial statements. The traditional approach to selecting indicators for accountancy analysis involves defining different aspects of company operations and an arbitrary selection of a few indicators which shed significant light on these aspects. If we look at many domestic and foreign textbooks, we see that different authors categorize indicators into similar but not entirely identical groups, which are intended to shed light on individual segments of company operations.

Amendments of accounting and other standards also affect the definition of indicators. Due to changes in the standard of financial reporting to AJPES, a few changes were introduced in 2006, involving definitions in the calculation of indicators. These changes were taken into consideration in the definitions of financial indicators between 2002-2005 and 2006-2009 sub-periods.

In accordance with the AJPES S.BON model methodology, a set of financial indicators was defined for individual risk factors affecting the occurrence of a payment default event, with the aim of finding the smallest subgroup of indicators which best reflect the individual risk factor for the occurrence of a payment default event by individual sectoral submodel.

2.1.1. Processing missing values of financial indicators

After the financial indicators were defined and the values calculated for each of the companies included in the analysis, we eliminated the problem of any missing values of financial indicators in individual observations.

Proper statistical procedure has helped us to eliminate the issue, so that there were no more missing values in financial indicator data.

2.1.2. Financial indicator transformation

Inclusion of explanatory variables into the model and their transformation are the two most important steps in the process of modeling payment default probability. In literature the following indicator transformations are used most often:

- categorization of the indicators;
- standardization and normalization of the indicators;
- use of sigmoid functions;
- use of non-parametric transformation;
- smoothing.

Transformation methods are used in order to achieve a monotonous correlation between an explanatory variable and the likelihood of payment default. Standardization is used as the most popular method of transformation, which means that the average value is subtracted from the observed values of the variable, and the difference is then divided by the standard deviation of the variable. Standardization enables the same measurement scale for all indicators, allowing direct comparison of assessed parameter values between indicators.

Simply using standardization does not solve the issue of non-normal distribution of observed variable values, as the variable is still asymmetrical despite standardization, with thicker tails, and the problem of nonlinearity. Other transformation are also possible, which attempt to solve the issue of nonlinearity (the determined correlation between the financial indicators and the likelihood of payment default is nonlinear, and may also be nonmonotonous), such as using polynomial approximations of the function, however this decreases the model transparency.

Because the correlation between financial indicators and the likelihood of payment default is usually nonlinear, and because logistic regression is based on a linear correlation, the nonlinear model needs to be linearized through transformations. However, the most suitable transformation function is not known in advance.

Upon reviewing professional theory and practice, we decided that AJPES S.BON model would use one of the transformation methods, which has been proven to be the most suitable after practical testing on data.

2.1.3. Selection of a smaller subgroup of financial indicators

We defined and tested a set of different financial indicators which reflect different risk factors for the occurrence of a payment default event separately by sectoral submodel. We checked, separately by sectoral submodel, how financial indicators, as the risk factor indicators of indebtedness, profitability, activity, productivity, growth, company size and liquidity, relate to the probability of a payment default event, and whether this correlation is consistent with theoretical expectations. We tested the following:

- sign of the correlation;
- form of the correlation;
- predictive power of financial indicators when forecasting the occurrence of a payment default event.

In the selection of the subset of the best financial indicators, separately by sectoral submodel, we used different statistical approaches. ***The forecasting power of the individual financial indicator in the sectoral submodel of the AJPES S.BON model was tested with the ROC curve and the AUC statistical measurement.*** The greatest distinctive power is observed in financial indicators where AUC statistics assume the highest values. AUC represents the measure of predictive power and, like any other statistic, is subject to random fluctuation caused by the sample data. ***Trust intervals were calculated using the AUC curve.***

2.2. Multivariate analysis – specification and assessment of model parameters

In the next step, financial indicators - transformed using the chosen transformation method - enter multivariate logistic regressions, which are applied to sectoral submodels with the aim of determining their multivariate predictive power in explaining the probability of a payment default event in companies belonging to specific sectors. There are various methods of statistical multivariate analysis which can be used for this purpose (discriminant analysis, logistic regression, probit model, neuron networks). ***Logistic regression was used to assess the parameters of the multivariate sectoral submodel of the AJPES S.BON model, as it has the least requirements regarding certain statistical assumptions of all the alternative methods.***

The advantage of using logistic regression is that it does not assume a normal multivariate distribution of independent variables and a linear correlation between the dependent and independent variable. It also does not assume homoscedasticity. However, it does require a sufficiently large sample. The main disadvantage of using logistic regression is its sensitivity to multi-colinearity. The result of its presence is a greater standard error in the assessment of the model parameters and a greater standard error of the projection.

The logistic regression model can be written as:

$$\Pr\left(y=1|\mathbf{x}\right)=F\left(\mathbf{x}'\boldsymbol{\beta}\right)=\frac{e^{\mathbf{x}'\boldsymbol{\beta}}}{1+e^{\mathbf{x}'\boldsymbol{\beta}}}$$

The logit model equation is often written as:

$$\text{logit}\ [\Pr(y=1|\mathbf{x})] = \mathbf{x}'\boldsymbol{\beta} \quad \text{with} \quad \text{logit}\ (p) \equiv \ln\left(\frac{p}{1-p}\right)$$

The assessment of the logistic regression parameters is based on the maximum likelihood method Let y_1, y_2, …, y_N represent a sample of N independent results of binary variables Y_1, Y_2, …, Y_N, where these are generated in the manner indicated by the latent regression model. The total probability of the observation (the so-called likelihood function=), depending on the value of the explanatory variables $\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_N$ and the vector of parameters $\boldsymbol{\beta}$, can be written as:

$$\begin{aligned} L &= \Pr(Y_1 = y_1, Y_2 = y_2, \ldots, Y_n = y_n | \mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N, \boldsymbol{\beta}) \\ &= \prod_{i:y_i=0}(1-F(\mathbf{x}_i'\boldsymbol{\beta}))\prod_{i:y_i=0}F(\mathbf{x}_i'\boldsymbol{\beta}) = \prod_{i=1}^{N}(F(\mathbf{x}_i'\boldsymbol{\beta}))^{y_i}(1-F(\mathbf{x}_i'\boldsymbol{\beta}))^{1-y_i} \end{aligned}$$

In the interest of mathematical simplification, we usually apply the natural logarithm of the likelihood function:

$$\begin{aligned} \ln L &= \sum_{i=1}^{N}(y_i \ln F(\mathbf{x}_i'\boldsymbol{\beta}) + (1-y_i)\ln(1-F(\mathbf{x}_i'\boldsymbol{\beta}))) \\ &= \sum_{i=1}^{N} \ln F(q_i \mathbf{x}_i'\boldsymbol{\beta}) \end{aligned}$$

where $q_i = 2y_i - 1$.

The vector of the optimal value of parameters $\boldsymbol{\beta}^*$ can be obtained by maximizing the logarithmized likelihood function in relation to the vector parameter $\boldsymbol{\beta}$ using the iterative numeric procedure (MLE method). Standardized assessors of the parameters of the maximum likelihood function b_i^* of the optimal parameter values β_i^* with consideration to the differences between the variances of explanatory variables is calculated as follows:

$$b_i^* = \frac{\beta_i s_i}{s_y}$$

β_i – non-standardized assessor of *i-th* parameter
s_i – variance of the i-th explanatory variable
s_y – variance of the ob dependent variable with the conditional value of Pr (y = 1)

After the model parameters are assessed, we use the **logit** equation $\Pr(y=1|\mathbf{x}) = F(\mathbf{x}'\boldsymbol{\beta}) = \frac{e^{\mathbf{x}'\boldsymbol{\beta}}}{1+e^{\mathbf{x}'\boldsymbol{\beta}}}$ to forecast the likelihood of payment default.

In order to ***determine goodness-of-fit*** of logistic regression, the Hosmer-Lemeshow (2000) test is used.

In order to ***determine the success of the logistic regression model*** we can use the so-called pseudo R^2 (Cox&Snell in Nagelkerke), which attempts to imitate the characteristics of the determination coefficient in linear regression (R^2).

In order to determine the statistic significance of the model as a whole we use the χ^2 likelihood ratio test, which helps us test whether all coefficients equal zero. The α value dismisses the null assumption and we conclude that at least one coefficient does not equal zero. The Wald test helps us determine the statistic significance of individual coefficients of the variables included in the model. Thus the statistically insignificant Wald test can help us eliminate certain variables from the model, helping us clear the model of any unnecessary and distracting variables.

2.2.1. Including financial indicators in the logistic model, assessment of the model parameters and selection of the optimal model

Before beginning the multivariate analysis we have a small subset of financial indicators which fit the economic criteria and have good univariate discriminatory power across individual subgroups of companies, collected depending on their industry. The indicators are transformed using the chosen transformation method.

Logistic regression, or the logit model, is used to assess the parameters of the multivariate sectoral submodels. In logistic regression we can apply several methods of including explanatory variables in the model. ***AJPES S.BON model employs the stepwise selection method.*** stepwise selection gradually includes and eliminates variables depending on their statistic significance. In the case of logistic regression the Wald test is used as inclusive or exclusive statistics.

In the process of including (transformed) financial indicators in the multivariate sectoral submodels, we need to check the stability of discriminatory power measured in AUC, the statistic significance and prefix of the coefficient of individual financial indicators included, and ensure good representation of all relevant risk factors or information categories.

When including individual financial indicators in the multivariate sectoral submodels we also need to take into consideration the correlation between them, since logistic regression is sensitive to the correlation between the explanatory variables. Including multiple mutually correlated explanatory variables in the model results in instability of the parameters and diminished model quality. Furthermore, the sign of the parameter can be contrary to economic expectations.

In multivariate logistic regression the issue of correlation between transformed indicators reflects as the issue of increasing the error of coefficient assessment and the error of assessment of the likelihood of payment default. Since, in addition to the AUC measure, a 95% confidence interval for the AUC measure was also calculated, the issue of potential correlation can be identified by analyzing the width of the intervals of the AUC measure.

We analyzed the results of a large number of differently specified multivariate logistic sectoral submodels. When selecting the optimal sectoral submodels we took into consideration the presence of various risk factors, the size of the AUC measure and the width of confidence intervals, the Hosmer-Lemeshow goodness of fit test, the Cox&Snell and Nagelkerke pseudo R^2 and statistic significance test of the model as a whole (χ^2 test).

2.2.2. Calculation of estimated likelihood of payment default for companies

The AJPES S.BON model sectoral submodel parameters are **assessed using the iterative procedure of maximizing the logarithmic maximum likelihood estimation (MLE) function**. Based on the assessed parameters and actual values of the (transformed) financial indicators included in the model for individual observation and with consideration to the sector to which it belongs, we calculate the likelihood of payment default for individual observation using the following logit equation:

$$\Pr\left(y=1\middle|\mathbf{x}\right)=F\left(\mathbf{x}'\boldsymbol{\beta}\right)=\frac{e^{\mathbf{x}'\boldsymbol{\beta}}}{1+e^{\mathbf{x}'\boldsymbol{\beta}}}$$

Chapter III

3. Calibration of the AJPES S.BON model and assignment of credit rating scores

Distinction between predictive power and model calibration is needed. The model can have great predictive power, yet is uncalibrated. On the other hand, a model can be calibrated, yet carry low predictive power. A model is calibrated if the average sample predicted likelihood of payment default for companies included in the analysis equals the long-term rate of payment default for the population from which the sample was selected. The goal is to create a model with a large predictive power, meaning that it is able to distinguish between good and bad companies while calibrated at the same time. It is significantly easier to recalibrate an uncalibrated model with high predictive power than improve the predictive power of a weak but calibrated model.

Basel standard requires banks to implement a robust system for confirming the accuracy of likelihood of payment default assessments. A significant portion of this confirmation process involves checking whether the average likelihood of payment default according to credit rating scores corresponds to the actual long-term rate of payment default. This is the so-called "level validation", which is subject to the effects of special data characteristics – e.g. that the data relates to a period characterized by a high correlation of payment default events or that this data does not refer to the entire macroeconomic cycle.

By evaluating the parameters of the multivariate sectoral submodels, available data can be used to assess the sample-dependent or uncalibrated likelihood of payment default for any company. This allows ordinal ranking of companies depending on their assessed likelihood of payment default. In the next step we calibrate the results with the long-term practically determined level of payment default, and finally we also calibrate the results with the credit rating scale with defined credit rating scores. If the calculated probability of a payment default event diverges significantly from the long-term average payment default rate, the model may be recalibrated in order for the calculated calibrated probability of a payment default may better reflect actual payment default rates.

The calibration procedure involves the following steps:

- calculation of average uncalibrated, sample-dependent probability of payment default;
- analysis of payment default rates for the Slovenian economy over a longer period of time and calculation of long-term annual payment defeault rate averages;
- calculation of calibration factors and their application to adjustment the uncalibrated sample-dependent conditional probability of payment default, resulting in calibrated payment default probabilities;

- determining the need for model recalibration in order for the calculated calibrated probability of a payment default may better reflect actual payment default rates.

For the purposes of calibrating the AJPES S.BON model we analyzed the changes in the rates of payment default in Slovenia in the period from 1994 to 2010. We analyzed the statistical characteristics of annual payment default rates, their fluctuation through the macroeconomic cycle and the calculated long-term average payment default rate.

3.1. Assignment of credit rating in relation to the calculation of calibrated likelihood of payment default

After calibration we gain access to sample-unconditional or calibrated payment default likelihoods for each individual observation. A number of credit rating categories need to be defined in order to create a credit rating scale system, with corresponding threshold values of payment default probability, which will serve as a basis for assignment of credit rating scores in each individual observation.

When reflecting the likelihood of default onto credit rating scores, we pursue the following goals:

- existence of a sufficient number of credit rating scores for the purposes of economic and regulatory application (***Basel II requirements***);
- distribution of credit rating scores across credit rating categories resembles normal distribution;
- none of the credit rating categories may include an excessive number of observation;
- credit rating categories are created in such a manner that the payment default rate for the individual credit rating category is constantly increasing from the poorest to the best credit rating category;
- the credit rating system must present a sufficient increase in the likelihood of payment default when passing from better to poorer credit rating scores, meaning there are no excessive gaps in the likelihood of payment default between two adjacent credit rating categories.

According to Basel II the likelihood of payment default may be classified into a maximum of 20 credit rating categories. Assigning a likelihood of payment default to the credit rating scores is key to satisfying the minimum requirements for the IRB approach under Basel II and the EU Directive. In order to satisfy these requirements, the credit rating scale must contain at least seven credit rating categories for payers and one credit rating category for non-payers, a total of eight credit rating categories.

The AJPES S.BON credit rating model sorts the payees into 10 credit rating categories according to their calculated likelihood of payment default. Based on the calculated thresholds we assigned individual companies credit rating scores depending on their calculated or calibrated sample-independent likelihood of payment default.

The AJPES S.BON model credit rating scale includes 10 credit rating scores for payers and one credit rating category for non-payers, i.e. companies in which a payment default event has actually occurred. The credit rating scores for payers comprise SB1, SB2, SB3, SB4, SB5, SB6, SB7, SB8, SB9 and SB10.[1]***. Companies in which a payment default event has actually occurred are assigned the credit rating score of SB10d. SB1 is the best credit rating score on the credit rating scale, and SB10 is the poorest on the credit rating scale.***

3.2. Credit rating score descriptions

The credit rating scores are defined on a scale of probability that a payment default event will occur in a specific case in the 12-month period following the date of the relevant financial statements upon which the credit rating score is based. The probability of the occurrence of a potential payment default event is lowest with the credit rating of SB1, increasing exponentially as we move towards the credit rating of SB10. The credit rating score of SB10d is assigned to companies in which a payment default event has actually occurred.

The average probabilities of payment default increase exponentially (not linearly) as they move from the best credit rating score of SB1 towards the poorest score of SB10. Despite the fact that more than one half of all Slovenian companies have a credit rating of SB5 or better, the exponentially increasing probability of payment default from one category to the next, the average likelihood of payment default in the 7th credit rating category (SB7) is roughly equal to the average likelihood of payment default for all Slovenian companies.

The average predicted likelihood of payment default for the first six credit rating scores (SB1, SB2, SB3, SB4, SB5, SB6) is thus lower than the overall average likelihood of payment default calculated for all Slovenian companies. The average likelihood of payment default in the seventh credit rating category (SB7) is roughly equal to the predicted average likelihood of payment default for all Slovenian companies. The average predicted likelihood of payment default for the credit rating scores SB8, SB9 and SB10 is significantly higher than the overall average likelihood of payment default anticipated for all Slovenian companies.

Table: Credit rating score descriptions

[1] The "SB" designation of credit rating scores and the corresponding number of the credit rating category derives from the umbrella name of the AJPES S.BON model methodology, and is an acronym for "Slovenian Credit Rating" ("slovenska boniteta").

Credit rating score	Description
SB1	SB1 is the highest score on the credit rating scale. A company which receives this rating has the best ability to settle its liabilities. The credit rating score is determined depending on its financial standing and creditworthiness. In companies with a credit rating score of SB1 the indicators showing the risk factors for occurrence of a payment default event suggest that the probability of a payment default event occurring, assessed by applying the model, is at the lowest level.
SB2	The company's ability to settle its obligations is very high. A company with an SB2 score is only slightly different from an SB1-rated company in terms of creditworthiness. Indicators showing the risk factors for the occurrence of a payment default event suggest that the probability of a payment default event occurring, assessed by applying the model, is very low, yet still higher than that in the first credit rating category.
SB3	The company's ability to settle its obligations is high. In companies with a credit rating of SB3 indicators showing the risk factors for the occurrence of a payment default event suggest that the probability of a payment default event occurring, assessed by applying a model, is low, yet still higher than that in the second credit rating category. Compared to companies with higher credit ratings, it is more sensitive to adverse changes in the business environment.
SB4	The company's ability to settle its obligations is still high, but lower than companies in the third credit rating category. Companies with a credit rating score of SB4 present indicators showing the risk factors for occurrence of a payment default event, which suggest that the probability of a payment default event occurring, assessed by applying the model, is still low. Regardless, on average, the probability of a payment default event in companies with a SB4 rating is higher than with those with a SB3 credit rating.
SB5	The company's ability to settle its obligations is still above average, but lower than companies in the fourth credit rating category. Adverse changes in the business environment or other unexpected events (shocks) can bring the company in a position where it will be unable to settle its obligations. Companies with a credit rating score of SB5 present indicators showing the risk factors for occurrence of a payment default event, which suggest that the probability of a payment default event occurring, assessed by applying the model, is lower than the overall average for Slovenian companies.
SB6	The company’s ability to settle its obligations is still above average, however, due to exponential increasing of the probability of payment

	default, about 60% of all Slovenian companies are ascribed a higher credit rating score. The company is still able to settle its obligations under normal market conditions, but is highly sensitive to changes in the business environment. Adverse changes in the macroeconomic environment or in the industry can put the company in a position where it will be unable to settle its obligations. Companies with a credit rating score of SB6 present indicators showing the risk factors for occurrence of a payment default event, which suggest that the probability of a payment default event occurring, assessed by applying the model, is still lower than the overall average for Slovenian companies, however, exponential increasing of the probability of payment default place it at a significantly higher risk than companies belonging to the fifth credit rating category.
SB7	The company’s ability to settle its obligations is average, however, due to exponential increasing of the probability of payment default, about 75% of all Slovenian companies are ascribed a higher credit rating score. Companies with a credit rating score of SB7 present indicators showing the risk factors for occurrence of a payment default event, which suggest that the probability of a payment default event occurring, assessed by applying the model, does not deviate significantly from the overall average for Slovenian companies. The company's business performance and its ability to settle obligations depend significantly on favorable conditions in the macroeconomic environment and the relevant industry, and the company can quickly find itself in trouble.
SB8	The company's ability to settle its obligations is very low and is significantly dependent on the conditions in the business environment. Any adverse changes in the circumstances are very likely to lead to a payment default event. Companies with a credit rating score of SB8 present indicators showing the risk factors for occurrence of a payment default event, which suggest that the probability of a payment default event occurring, assessed by applying the model, is high and it is at a significantly higher risk than companies belonging to the seventh credit rating category due to exponential increasing of the probability of payment default.
SB9	The company's ability to settle its obligations is very low. Companies with a credit rating score of SB9 present indicators showing the risk factors for occurrence of a payment default event, which suggest that the probability of a payment default event occurring, assessed by applying the model, is very high and it is at a significantly higher risk than companies belonging to the eighth credit rating category due to exponential increasing of the probability of payment default. In normal

	circumstances in a business enlivenment a company with a credit rating of SB9 is barely able to settle its obligations.
SB10	The company's ability to settle its obligations is at the lowest level across all Slovenian companies. Companies with a credit rating score of SB10 present indicators showing the risk factors for occurrence of a payment default event, which suggest that the probability of a payment default event occurring, assessed by applying the model, is at the highest level and it is at a critically higher risk than companies belonging to the ninth credit rating category due to exponential increasing of the probability of payment default. For companies with a credit rating score of SB10 there is the greatest probability that the company will be unable to settle one or more of its obligation during the 12-month period following the date of the financial statements.
SB10d	A credit rating score of SB10d is assigned to companies in which a payment default event has actually occurred, i.e. bankruptcy, liquidation or compulsory composition proceedings.

Source: own definitions.

3.3. Transition matrices

A credit rating score assigned to a company changes through time. The change is the result of constant updating of credit rating scores, and the corresponding regulatory requirements. ***Basel II requires that the credit rating requirements are updated at least once per year, and more often if events occur from which we can reasonably assume the credit risk has increased.*** This improves the identification of risk, and helps us test the validity of credit rating models.

One annual transfer matrix is created by identifying the credit rating scores assigned to all companies subject to assessment over a 12-month period. All changes of credit rating scores during this period are counted, providing absolute frequencies of transition.

The transition matrices are specific to the individual credit rating model and reflect the likelihood of transition from an existing credit rating score (presented in columns) into other credit rating scores (presented in rows) in a given time period.

Due to the characteristics of the construction of the transition matrix observations are concentrated along the diagonal (unchanged credit rating), then the density of observation decreases as the distance from the diagonal increases. The concentration power along the diagonal also depends on the number of credit rating categories formed and the stability of the reflection onto the credit rating scale. The more credit rating scores exist on the credit rating scale, the higher the number of transition.

Chapter IV

4. Model validity testing

Model validity testing must involve the monitoring of predictive power and model stability, analyses of model correlations and testing the results predicted by the model compared to the actual results in terms of occurrence of a payment default event. The Basel II approach requires that the model validity testing process is described in the documentation accompanying the credit rating model. This explicit requirement indicates the importance of model validity testing at the model development level. Testing must also include testing outside the observation sample, as well as testing outside the time of observation, indicating the quality of the model using unknown data.

In statistical models quantitative testing represents a part of model development. Regardless, statistical credit rating models require use of data obtained through practical use of the model in order to perform quantitative model testing. benchmark data may be used as a substitute. This especially applies when the same sample is used to check the quality of a large number of models.

The key criteria which need to be checked in quantitative model validity testing include:

- the model's discriminatory power,
- accuracy of model calibration and
- stability of the model outside the sample and time of observation.

The discriminatory power of the model means its ability to distinguish, on an ex-ante basis, between companies where a payment default event will occur in a given time horizon and companies where the payment default event will not occur. This is the so-called quality of classification.

Model validity testing must also be performed on an independent database, i.e. outside the sample and time of observation. Otherwise over-fitting can occur on the existing data sample, resulting in poor distinguishing power inside the observation sample. In other words, this means that the credit rating model has low stability. A stable credit rating model is characterized by a good correlation between credit rating risk and individual risk factors, even within the development sample, meaning that the found correlation is not merely the result of the selected data sample. This correlation and consequently the quality of the model is preserved through time, as well.

Calibration quality depends on the (dis)similarity of calibrated likelihoods of payment default with actual rates of default observed in practice. Verifying the calibration of the credit rating model is often called "back-testing".

Chapter V

5. Updating of credit rating scores

5.1. Credit rating score update due to the ocurrence of a payment default event

Credit rating scores are determined once per year based on submitted annual financial statements. Credit rating scores based on 2010 financial statements include a calculation of likelihood of individual companies incurring a payment default event within a year (i.e. in 2011).

Even after assigning annual model credit rating scores using the AJPES S.BON model, we can keep track of payment default in companies on an ongoing basis. Model assessments obtained on the basis of financial statements are therefore constantly updated based on actual data upon occurrence of a payment default event. If a company was assigned a credit rating score based on its 2010 financial statements (e.g. SB9), then actually became a non-payer on a given date in 2011, the credit rating score is updated from SB9 to SB10d on that date.

5.2. Credit rating score updated due to deterioration of the company's short-term solvency

In order to ensure that credit rating scores reflect as much as possible all available information about the company's ongoing business operations which we can use to determine its short-term solvency, the credit rating scores ascribed on the basis of the company's annual report are also updated mid-year, or after being ascribed based on the annual report.

Mid-year updates of credit rating scores are based on information about transaction account suspensions and court announcements for the relevant company and its associated companies, or for the group.