METHODOLOGY FOR ASSIGNING DEBENTURES CREDIT RISK PROFILES

CONTENTS

EXECUTIVE SUMMARY

On November 30, 2018, 1,451 debentures were deposited at B3. These bonds were issued by 665 companies from dozens of Brazilian industries. The total value of those debentures was approximately BRL425 billion.

However, liquidity in the secondary debentures market was limited. On average, only 80 debentures were traded daily at B3. Only two were traded on all trading sessions in the 12 months prior to the survey. The average daily traded value was around BRL250 million. Excluding debentures held in treasury and those issued by leasing companies, a good estimate is obtained of the value that could be traded in the secondary market: BRL334 billion. The average annual daily turnover of the secondary debentures market, however, is limited to 18%.

With due regard for comparability, the turnover of the cash market in Brazil is 160%.

With the purpose of developing the primary and secondary debentures market in Brazil, B3 now **calculates the reference prices for public debentures on a daily basis**. This rule is governed by the Brazilian Securities and Exchange Commission (CVM) Instructions No. 400 and 476. Prices for the following debentures are not calculated: perpetual and convertible debentures that incorporate interest on the principal; debentures issued by leasing companies; debentures from issuers that do not disclose their accounting information or whose accounting information are out of date; and debentures from holding companies whose equity holdings are not clearly identified. In this methodology, we will calculate prices only for those projects undergoing the pre-operational phase or under development with shareholder guarantee.

Following international empirical evidence, it is expected that the disclosure of reference prices will be useful to the price discovery process of these assets, thus boosting investor confidence and trading volumes.

B3's methodology for calculating the debentures reference price is based on trading in the primary and secondary markets and the credit risk profile assigned to the debentures. The methodology contains mark-to-market and mark-to-model aspects.

This document describes **B3's methodology for assigning credit risk profiles.**

CVM Instruction No. 521 establishes the credit risk rating – defined as the activity of opining on the credit quality of an issuer of equity or debt bonds, of a structured transaction, or of any financial asset issued on the securities market – is the private activity of a credit risk rating agency registered with CVM if it is an agency based in Brazil. Credit risk rating agencies are those that professionally undertake a credit risk rating activity within the securities market.

CVM Instruction No. 521 only applies to credit risk ratings intended for publication, disclosure or distribution to third parties, even if restricted to customers.

B3 is not a credit risk rating agency and, therefore, the pricing activity should not be treated or interpreted as a credit risk rating, especially for the purposes of CVM Instruction No. 521. Such activity is strictly for internal consumption within the scope of debentures pricing and, thus, the credit profiles produced by B3 will not be disclosed. However, B3 may discuss with market participants particular cases whereby assignment of the credit risk profile based on the methodology described herein and public domain information is carried out immediately. Such are cases, for example, of debentures in default or undergoing court-supervised reorganization.

1 INTRODUCTION

The starting point for B3's pricing methodology is the breakdown of the discount rates of the debentures' cash flows to calculate their respective values, which are found in two major components:

- Risk-free interest rate relating to its index. This rate is derived from daily settlements of futures contracts on the index and represents essentially the mark-to-market; and
- Spread corresponding to its credit risk. Interest rate that must be added to the risk-free interest rate to yield the debenture's interest rate. It represents the premium required by investors to face the debenture's credit risk[1]. To calculate the spread, a credit risk profile should be assigned to all debentures. For this, B3 uses its own proprietary methodology.

After calculating the credit risks, all debentures are grouped by this variable. Thus, debentures with similar credit risk levels are assigned the same risk profile.

Interest rate curves are estimated on a daily basis for each risk profile based on the traded debentures. The difference between the interest rate curve and the index curve results in the spread curve for each profile.

Since debentures that were not traded on a given day also have their credit risk calculated, each debenture is associated with the credit spread curve of its risk profile by using the credit spread on that day as if it were the date of its own issue.

Based on the credit spread assigned to the debenture and the risk-free interest rate of its index, its discount rate is obtained. The reference price is the result of the debenture's cash flow discounted by that interest rate.

The credit risk profile is associated with the debenture's **default probability**. More specifically, it is the risk that the issuer will not honor their **payments, in Brazilian Reais, within 12 months after** the evaluation date. Thus, the profile refers to the comparability between companies and issuances in Brazil. There is no international comparability.

[1] This component may also contain other risk premiums, the most common being liquidity risk.

The methodology considers three groups of variables, the first two being associated with the **issuer** of the debenture, and the third variable, with the characteristics of its **issuance**.

The first type comprises variables that capture the **business's risk profile**, highlighting the following: jurisdiction, economic activity sector and issuer's positioning in its sector, regulatory risk, the structure of the economic group in which the company is included, governance, and business strategy.

The second type encompasses variables that capture the **issuer's financial risk profile**, highlighting the following: cash flow characteristics, profitability, financial structure and flexibility, and credit bureau information. In this group, for the variables based on financial information, we included a relativization by comparing the issuer's observed value with the sector's observed value (median). In doing so, we were able to introduce the issuer's view of its sector peers, while respecting the dynamics of each sector.

The third type encompasses variables that capture the debenture's **issuance characteristics**, highlighting the following: protection clauses for creditors (cross-default, financial covenants, sureties, etc.), seniority and subordination.

Due to the large number of issuers, this methodology seeks, whenever possible, to rely on quantitative methods for assessing credit risk.

The methodology has four sequential components:

i. Statistical model for estimating the default probability;
ii. Statistical model for adjusting the default probability due to macro-sector factors;
iii. Assignment of a credit risk profile by grouping similar default probabilities;
iv. Qualitative adjustments to profiles.

Initially, the (i) debenture's default probability is estimated by a logistic regression that explains binary events, nondefault or default, through variables of the three types described above. In fact, the model estimates a probability of future default, as the explanatory variables refer to periods prior to the one in which the default may materialize. This model is similar to score models used internally by institutions with credit portfolios containing a high number of issuers and is described in item 3 (Estimating Default Probability[2]) of this document.

The time lag of the model's explanatory variables described in item 3 tends to reduce the accuracy of estimated default probabilities. One way to mitigate this effect is to adjust the default probabilities to incorporate forward-looking conditions expected for the period in which default may occur. To this end, B3 uses a forward-looking adjustment on issuers belonging to similar economic sectors. This methodology refers to (ii) statistical model for adjusting the default probability due to macro-sector factors. For each macro-sector, the default probabilities are adjusted by means of macro-economic variables forecast that jointly impact issuers during the period in which the default may materialize. This adjustment is described in item 4 (Macro-sector Adjustment of Default Probability) of this document.

The third and last quantitative component of the methodology is (iii) assignment of a credit risk profile by grouping similar default probabilities. Default probabilities are ranked from lowest to highest and grouped according to the risk level. Each group is assigned a credit risk profile with a letter indicating its credit quality. The creation of a risk scale is described in item 5 (Credit Risk Profile Assignment) of this document.

If situations are identified whereby the quantitative approach is not sufficient, credit risk profiles can be changed to a level above or below due to qualitative factors, the fourth component of the methodology. To control the risk of subjective decisions, they are subject to strict governance. The qualitative adjustment process and its governance are described in item 6 (Qualitative Adjustments) of this document.

Following the methodology summarized above and described in more detail below, B3 assigns credit risk profiles to public debentures on a daily basis, as defined above.

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[2] If the number of issuers were substantially smaller, it would be possible to construct the model's explanatory variables in such a way as to include the period in which the default might occur. For example, balance sheet variables could be forecast for the 12-month period ahead.

2 ELIGIBLE COMPANIES

The universe of debentures ranges from large publicly held companies to small privately held companies, for which little information is available, and from private issues to public issues.

In order to assign a credit risk profile, issuers must meet certain conditions specified below:

- They must have made at least one public issue; since the methodology comprises assessment of payment of issues, only when there is a public issue is it possible to assess an issuer;

- They must prepare financial statements, which is a valuable source of information to assess a company's credit risk.

Given the quantitative model profile developed for the methodology, the following additional conditions were necessary for eligibility purposes:

- Companies must not have Greenfield-stage projects underway (construction or ramp-up phases), since the quantitative model is anchored in financial statements that are not significant for Greenfield projects; and

- Companies must not be in the Securitization or Leasing segments, or related to the financial system, as the evaluation criterion for assigning credit risk profile for these companies is different from the criterion used for corporate companies.

Whenever a debenture issuer is found not to be suited to the proposed solution, that issuer will not be eligible for credit risk profile rating assignment.

For significant market cases involving issuers with a high volume of trades who are not eligible, an override credit risk profile is assigned. This will be defined in the next items of this methodology described below.

3 ESTIMATING DEFAULT PROBABILITY

Logistic regression is used to model the debentures' default probability. This methodology estimates the value of a binary categorical variable from a series of explanatory variables. In the present case, the dependent binary variable represents the bond's nondefault or default status.

Let us assume $P(A)$ is the probability of occurrence of event A. Y is the binary categorical variable that indicates 1 for the occurrence of a default event and 0 for a nondefault event, and X is the set of explanatory variables.

Each explanatory variable is discretized into categories according to their values. The "issuer's existence" variable, for example, can be discretized into four categories: issuers with less than 5 years of existence; between 5 and 15 years; between 15 and 25 years; and over 25 years. Each issuer may belong to only one category per variable. In fact, the model's regressors are the categories.

The model is estimated from monthly data for all available nondefaulting debentures.

Let us assume *N* is the total number of categories resulting from the discretization of all explanatory variables for month *t*. The logistic regression explains the nondefault probability of debenture *d* in the period between the months $t+1$ and $t+12$ through the *N* groups, according to equation (1):

$$P\left(Y_{d,t+12} = 0/Y_{d,t} = 0\right) = \frac{e^{\sum_{i=0}^{N} \beta_i I_{i,d,t}}}{1+e^{\sum_{i=0}^{N} \beta_i I_{i,d,t}}} \qquad (1)$$

Where:

- *Y* is the binary categorical variable indicating 1 for the occurrence of a default event and 0 for a nondefault event;
- β_0 is the regression intercept;
- $\beta_i \; 1 \leq i \leq N$ is the linear coefficient relating to each group;

- $I_{i,d,t}$. $1 \leq i \leq N$ is the i explanatory variable for debenture *d* to belong at the time *t*.

Each month of the estimation sample, the nondefaulting debentures contribute with their explanatory variables and with the information that they have either been in default or nondefault in the following 12 months. Thus, an issuer may contribute with several observations for the estimation. Each month in the estimation is called a **development month**.

Equation (1) is estimated by maximizing the likelihood function. Default is observed in the 12 months following t ($Y_{i,t+12}$) and the explanatory variables (I_i, $1 \leq i \leq N$) are in the issuer's view ($I_{i,d}$) available in month t ($I_{i,d,t}$).

Note that an initial condition is that at the time t, the issuer is not in default ($Y_{d,t} = 0$), and that is precisely why it must not be considered a 'bad debt at origin'. Further details on this can be found in item 3.1. Definition of default event and 'bad debt at origin' concept of this document.

The following example illustrates the high level model, considering a model with four variables. The estimation resulted in the values described in Table 1.

Table 1 – Betas illustrating a credit model

β_0	β_1	β_2	β_3	β_4
-6.18	3.19	2.66	1.27	1.67

The sum of the betas is 2.61. When we replace this value in equation (1), the nondefault probability is 93.2%. Therefore, the default probability is 6.8%.

With each model estimation its sample will be expanded to include the most recent period possible. The start of the estimation sample, however, is set at January 2015. This is the month after which there is sufficient data for reliable statistical estimation.

This topic consists of two sub-items. The first subitem defines the default event. The second describes the variables selection process.

3.1 Definition of default event and ‘bad debt at origin’ concept

A debenture issuer is considered to be in default when it fails to make an amortization or interest payment within the last three events during a future 12-month window on the evaluation date. If the default occurs, $Y_{d,t+12}$ will be equal to 1. Otherwise, $Y_{d,t+12}$ will be equal to 0.

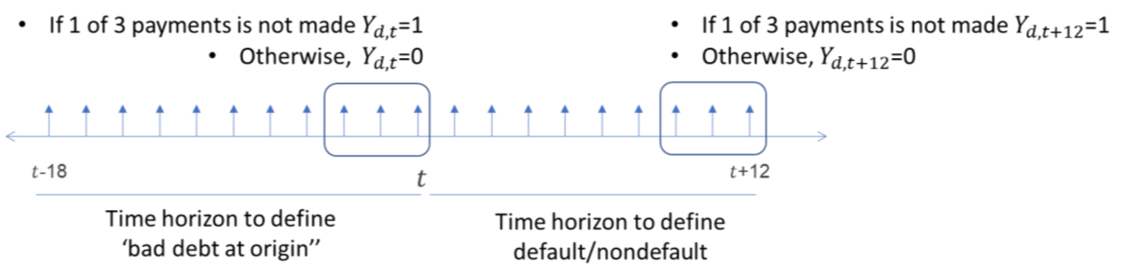
As noted earlier, at the time *t* the issuer should not be considered in default (or 'bad debt at origin'), namely, $Y_{d,t}$ must be equal to 0. Otherwise, there is no need to estimate a default probability since the issuer is already in default.

An issuer is considered 'bad debt at origin' if it presents at least one interest or amortization non-payment among the last three amortization/interest payments within the last 18 months, considering all debentures linked to those payments.

The option for the past 18-month window occurs as some debentures have annual payments. Therefore, the non-payment effect might bring about a situation occurred during a time horizon that is too far from the present time.

The option to consider all debentures linked to that issuer, the so-called ‘drag’, is due to the fact that the risk is assigned to the issuer’s view.

The sketch below will help to clarify the ‘bad debt at origin’ and ‘default’ concepts.



3.2 Selection of variables ($I_{i,d,t}$)

The initial set of variables that are eligible to compose the model must have aspects that capture the debenture issuer’s business and financial risks and the issuance characteristics.

Since the number of variables available is large – in the first version of the model, the initial set had approximately 2,000 variables – a well-defined selection process is needed.

The variables selection process is sequential and is divided into three stages: (i) univariate, (ii) bivariate and (iii) multivariate.

The (i) univariate stage seeks to select explanatory variables that meet the following characteristics:

- Correlation with the dependent variable that is statistically significant and makes economic sense;
- Low ratios of null values;
- Is stable over time;
- Is available when estimating the model;
- Has significant discriminatory power.

The variables selected at the univariate stage pass on to the (ii) bivariate stage. During this phase, the behavior of an explanatory variable in the presence of another variable is analyzed to avoid collinearity problems in the model. For this purpose, the correlations between explanatory variables and between these and the dependent variable are calculated. If two explanatory variables have a correlation in absolute value above a certain threshold, the variable that has the lowest correlation in absolute value with the dependent variable is discarded.

At the end of the bivariate stage, the selected variables were treated in order to meet linearity relationships in the logistic equation. The form adopted was categorization of variables, which for a continuous variable means defining ranges (for example, leverage between 1.5 and 2 to define a category) and for variables that are already categorical or ordinal variables, it means groupings of categories or ordinations.

It is important that such classification respects the variable concept (for example, for an ordinal variable whereby the A, B and C position is an ordination which does not have category A and B together and category C separated) and that it respects the monotonicity of the default rate (for example, that the 1.5 to 2 leverage category has a lower default rate than the 2 to 2.5 leverage category).

This process alone is a selection of variables. Only variables with monotonicity of the default rate and at least two stable categories over time were selected for logistic regression.

Finally, the (iii) multivariate process consists of estimating β_i by logistic regression. The selected variables must have statistical significance (significant p-value). Thus, we have a $I_{i,d,t}$ universe of explanatory variables determining an equation equivalent to (1).

The construct of the model involves creating some possible models in the (1) equation model, each with an $I_{i,d,t}$ set of explanatory variables. The selection among the possible models is done by evaluating:

- KS, GINI, BIC: Metrics that estimate which solution has the greatest discriminatory power, i.e., can better separate defaulting individuals from nondefaulting ones.
- KS, GINI and BIC performance in test months: A portion of the available data, in general the last months of sample t, are excluded from β_i estimation. For this audience, the estimated models are applied to evaluate the discrimination metrics and assess which equation, in addition to having a good separation power in the development sample, is also capable of discriminating in external samples, thus showing more robustness as a predictive model.

4 MACRO-SECTOR ADJUSTMENT OF DEFAULT PROBABILITY

Due to the high number of issuers, there is a time lag between the explanatory variables of the logistic regression referring to month t, and the nondefault/default event for the 12 months ahead. Such a lag tends to reduce the accuracy of default probabilities.

One way of addressing this problem is to adjust the default probabilities so that they incorporate expected forward-looking conditions for the period in which the default may occur and also to affect groups of sectors in a similar manner.

Once again, the number of issuers is an important decision element in building the credit risk profile methodology. If, on the one hand, a high number of issuers makes the forward-looking adjustment sectorial, on the other hand, a limited number of issuers in certain sectors causes the forward-looking adjustment to be applied to groups of sectors.

To preserve the objective nature of B3's credit profile assignment methodology, the forward-looking adjustment occurs through two quantitative steps described below.

In the first step, issuers belonging to sectors that respond similarly to macro-economic variables (such as inflation, interest rates, economic activity and exchange rate) are grouped into macro-sectors. Some examples of macro-sectors include consumption, agriculture and infrastructure.

For each macro-sector, a regression models the average default probability observed by the average default probability estimated by the logistic model and by forecasts of macro-economic variables for the future period in which the default event may occur.

In order to minimize the subjective nature of B3's credit profile assignment methodology, the source of forecasts for macro-economic variables is the Central Bank of Brazil's Market Expectations System (Focus). Click here to view.

Finally, in the second step the default probability of each issuer is corrected based on the estimated macro-sector model and on a Bayesian transformation model that distributes the macro-sector adjustment proportionally to each issuer's risk.

5 CREDIT RISK PROFILE ASSIGNMENT

The debentures' default probabilities are estimated by logistic regression and then adjusted quantitatively and prospectively by macro-economic factors.

The third component of the methodology is the (iii) credit profile assignment itself. For this purpose, debentures are ranked by their default probabilities in an upward manner and grouped by similarity of these values. Each group is assigned a letter that represents its credit profile: the closer to the beginning of the alphabet, the better its credit, and therefore, the lower its default probability. In fact, the credit profile represents a discretization of the default probability.

From a credit standpoint, the groups must present the following characteristics over time:

- The group must have good stability;
- The average default probability of a group with a higher (lower) credit profile must always be lower (higher) than the average default probabilities of groups with lower (higher) credit profiles;
- Migration between groups must be smooth.

Given that the credit profile assignment methodology is part of the debentures pricing methodology, the latter impacts the former in terms of choosing the number of credit profiles. As each profile needs to be associated with a spread curve estimated on a daily basis, the limited trading liquidity on the secondary debentures market restricts the number of credit profiles.

Considering the factors described above, seven credit profiles were chosen for the first version of the methodology. In addition to the four profiles shown in Table 2 (A, B, C and C-), the credit risk rating scale includes three other profiles: D, E and F.

Profile D is assigned to issuers in default ('bad debt at origin') at the time *t* or undergoing court-supervised reorganization; profile E is assigned to issuers undergoing court-supervised reorganization and whose respective recovery plans have not been approved within the legal term or are not being complied with under the conditions approved by creditors; and profile F is assigned to issuers that are undergoing liquidation process or closing down their business activities.

Table 2 – Credit risk profiles in the first version of the methodology

Profile	Average default – model's development period
A	3%
B	7%
C	22%
C-	43%

6 QUALITATIVE ADJUSTMENTS

Qualitative adjustment consists in improving or worsening the credit risk profile assigned by quantitative methods for cases whereby relevant information is not captured in a timely manner by those methods.

The application of such adjustments follows strict governance rules, since they directly reflect subjective evaluation. The first governance element is the collegiate nature of decision-making. Decisions on qualitative adjustments are the responsibility of the **B3 Private Fixed Income Pricing Work Group**. The second governance element is the **Qualitative Adjustment Rule for Credit Risk Profiles**, which describes the guidelines to be followed in the evaluation.

Details of the qualitative adjustment rules are described below.

6.1 Pre-defined qualitative adjustments

a. Assignment with indication of court-supervised reorganization

There are companies that file for reorganization without presenting debentures default events. Therefore, when a company submits a request for court-supervised reorganization, if it is not in the D default risk profile observed, it is qualitatively assigned the D profile.

b. Greenfield projects with real and irrevocable guarantee

Many early stage projects have secured debentures (shareholder) so that the entire credit risk (default) of the issue is linked to the guarantor's credit risk. In general, this information is available in the debenture deeds and is not a structured data to be captured quantitatively by the methodology. Therefore, once the guarantee is confirmed with the due enforcement of risk transfer for the guarantor, the issue in question begins to receive the guarantor’s risk profile. When more than one guarantor is available (joint guarantees), a riskier risk profile among guarantors is assigned to the issue.

6.2 Additional qualitative adjustments

Although the model is structured and shows excellent adherence in forecasting the observed average probability, there are subjective factors that are not captured in a quantitative way and which can generate a more accurate credit risk profile assignment. Some of these factors include:

- Shareholders can be excellent credit risk mitigators and they can also be factors that increase the chance of default,
- Market positioning: A sector with greater competition and greater dependence on external factors to the company's figures can increase a company's credit risk,
- When the issuer has excessive amendments and presents a risk profile adhering to a 'forced reorganization', and
- News disseminated in the media.

In some cases, an in-depth assessment of the issuing company is made and the need to adjust the credit profile assigned quantitatively is assessed.

6.3 Application

The assignment of pre-defined qualitative adjustments incorporates the methodology and is the responsibility of Credit Risk (the so-called methodology overrides).

Additional qualitative adjustments, on the other hand, require the approval of a multi-task work group in addition to a forum for presenting the evaluation.

Any change made through the qualitative stage is considered an override and has an assignment date and an expiration date, usually six months.

The return of the credit profile to that assigned by the quantitative stage can be done before the expiration of the override, if it is found that the conditions that led to the qualitative marking of the risk profile are no longer in effect.

CHANGE LOG

Effective: April 8, 2019

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2nd version: April 20, 2020

Areas responsible for the document

Responsible for	Area
Draft	Analytics and Credit Risk
Review	Credit Risk
Approval	Risk Management

Updates

Version	Item Changed	Reason	Date
1	Original Version	N/A	N/A
2	Adjustments to the text on all topics. Change to Table 2 in item 5 due to the development of a new equation. Topic 6 fully detailed.	New version of the model (August 2019). Improvement to the application of qualitative adjustments.	April 20, 2020
3	Adjustments to the text Topic 6	Text review	April 29, 2020