5

SME Credit Rating Models: A New Approach

This chapter describes the methodology and the estimation and validation process of a proprietary SME Credit Rating Model (DefaultMetrics™ 2.0) developed by Capital Investment S.r.l. based on mid-corporate and SME commercial bank databases. The accuracy of the model relies on the integration of accounting information and behavioral information. The related modeling incorporates the author's 20-year experience in applied research and in modeling customer–bank relationships. This model gains leverage on data from the Italian CCR, which is strongly predictive of default events as explained in this chapter and in Sects. 4.6, 4.7, 4.8, and 4.9.

5.1 Definition of Default

The model estimates the probability of default over the 12 months following the moment a company's creditworthiness is assessed.

The definition of default, whereby a counterparty is defined as solvent (good) or insolvent (bad), is that established in the Basel II and Basel III regulations, largely based on bank-specific and CCR data.

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With regard to the provisions set out in the supervisory regulations in force, defaulted exposures pursuant to the regulations are defined as:

1. substandard loans; and/or
2. bad loans; and/or
3. restructured loans; and/or
4. exposures past-due on a continuing basis.

More specifically, the following regulatory definitions apply:

1. Substandard loans: on- and off-balance sheet exposures to borrowers facing temporary objective difficulties which may be expected to be remedied within a reasonable period of time;
2. Bad loans: on- and off-balance sheet exposures to borrowers in a state of insolvency (even if insolvency is not legally ascertained) or in essentially equivalent situations, regardless of any loss forecasts made by the bank;
3. Restructured loans: on- and off-balance sheet exposures for which a bank (or a pool of banks), as a result of the deterioration of the borrower's financial situation, agrees to amendments to the original terms and conditions, giving rise to a loss;
4. Past due on a continuing basis (or abnormal past due, to be distinguished from short-term, natural past due): the company's exposures are past due and/or overdrawn for more than 90 consecutive days and do not normalize in the following months. For the purpose of determining the amount of past due and/or overdrawn exposures, such exposures on some credit lines may be offset with margins available on other existing credit lines granted to the same borrower.

One of the following two values is equal to or greater than the 5 % threshold:

1. Average past due and/or overdrawn amounts out of the entire exposure, measured on a daily basis over the previous 90 days;
2. Past due and/or overdrawn amounts out of the entire exposure measured as of the 180th day (since the loan has become past due and/or overdrawn).

For the purpose of calculating materiality in the numerator:

1. Any amount that is past due by less than 90 days with respect to other exposures must be taken into account;
2. Any default interest claimed from the customer must not be included.

In calculating the denominator, securities must be accounted for on the basis of their book value; other loans must be accounted for on the basis of their cash exposure

The default definition is very clear from a regulatory point of view. All 90-day past dues that generate a loss given default (LGD) greater than zero must be considered as default (bad company). However, in several banking markets not all 90-day past dues generate an LGD greater than zero.

A clear separation must be drawn between 90-day past dues that do not generate a LGD greater than zero (or past dues associated with a 100 % cure rate) and 90-day past-dues that generate an LGD greater than zero (past dues associated with a 100 % danger rate). With regard to Basel regulations, the former (false past dues) are not to be considered as default whereas the latter (true past dues) must be considered as default (Fig. 5.1).

It is simple to demonstrate that if false past dues (with a 100 % cure rate) are also taken into account in capital requirements, the excepted loss does not change, while the unexpected loss (or capital requirement) decreases dramatically; this is due to Basel algebra.

The process of collecting and examining past due data requires great attention and scrutiny in the cleaning and validation of the data. It is necessary not only to identify the past due event, but also to determine whether this event has subsequently generated an economic loss (LGD>0) or has not generated an economic loss (LGD = 0).

Only past due events which, subsequent to their capture, have generated an economic loss should be considered true defaults and designated as bad. If this approach is not followed, especially in EU fringe countries, there will be a phenomenon of inflated false bads, which dilutes both the predictive capacity of rating models and also the savings on capital requirements.

In balanced development samples, only true 90-day past due exposures were considered as “bad” enterprises. These were 90-day past dues associated with an LGD greater than zero; that is, those which subse-

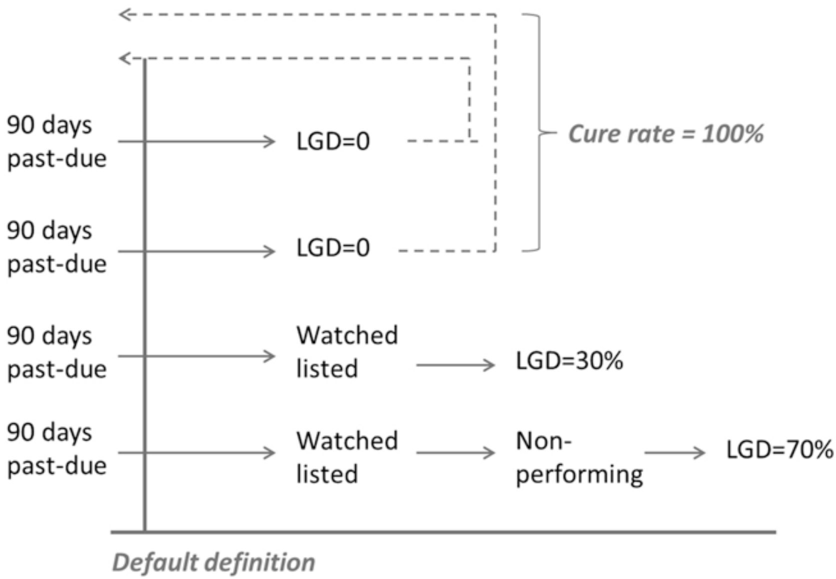

Fig. 5.1 90-day past dues with 100 % cure rate are different from 90-day past dues with 100 % danger rate

quently deteriorated, falling into a substandard, bad or restructured loan classification.

5.2 Data Description

5.2.1 Data Exclusions

Default characteristics must be similar for the firms and industries treated in the model. The data does not include financial institutions – that is, banks, insurance companies and investment companies – in order to improve the accuracy ratio. This exclusion is due to the fact their balance sheets present higher leverage compared with private firms; also, their regulation and capital requirements set them widely apart from middle-market companies. Other companies excluded from the data are:

1. Holding companies with no operating activity: In estimating the credit risk of such businesses, the lending activity of which is asset-based, accounting information is not as relevant as the value of their assets.
2. Real estate developers and investment companies: Since the activity of such companies centers on asset-based rather than cash flow-based lending, less information on credit risk is found in the annual their profit and loss accounts.
3. Public and not-for profit institutions: The financial results of public institutions cannot be compared with those of private institutions. Likewise, the financial ratios of not-for-profit and for-profit institutions are very different.
4. Companies whose net sales are below €2,500,000 are not included due to the lesser value of their accounting information, along with the greater value of information from the CCR with regard to estimating credit risk.
5. Companies in the first two years of existence: Given the high volatility of financial data for these companies, such data cannot be used to evaluate their creditworthiness.

5.2.2 Descriptive Statics of the Data

The model is designed to estimate the default risk of companies with a production value ranging from €2.5 million to €100 million.

5.2.2.1 Overview of the Data

The model has been developed and validated using an extensive data set of Italian companies' balance sheet and CCR information.

Figure 5.2 presents the distribution of Italian firms and defaults used in validation and calibration: about 147,000 units of information for the period 2008–2012 were sourced; a unit of information means either a balance sheet or a firm's CCR status (Source: Capital Investment Research).

Fig. 5.2 Date distribution of Italian units of information and default data

5.2.2.2 Robustness of the Data

The data set used in the construction and validation of the model is extremely broad and representative of the real circumstances in which Italian SMEs operate, in terms of their sector of activity (Fig. 5.3) as well as their geographical location (see Fig. 5.4). The number of defaults examined in the analysis is equally representative of real conditions.

5.2.3 Cleaning the Data

Data cleaning was a key process in the development of the model, and is necessary to better define input variables and improve the accuracy ratio. Great attention was paid to:

- the correct identification of what is and what is not a proper regulatory default (see Sect. 2.3 for the definition of default);
- the correct reading CCR data;

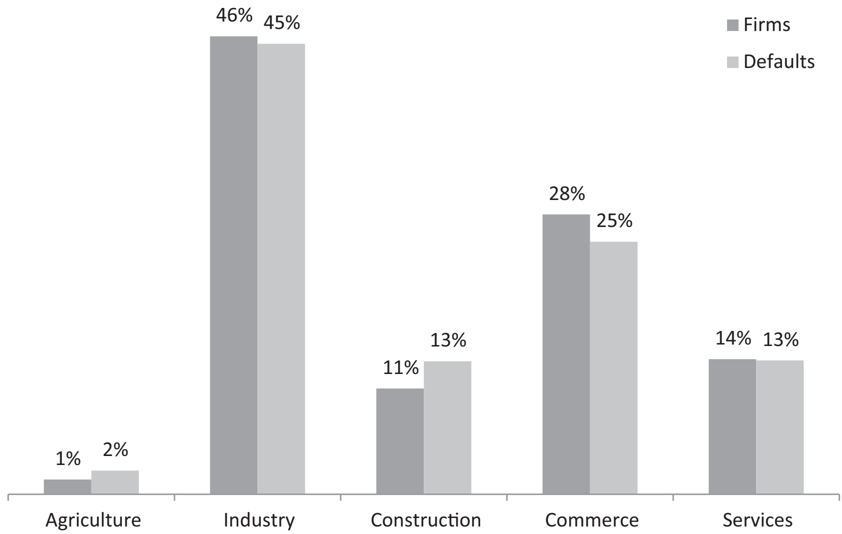

Fig. 5.3 Distribution of Italian defaults and firms by industry

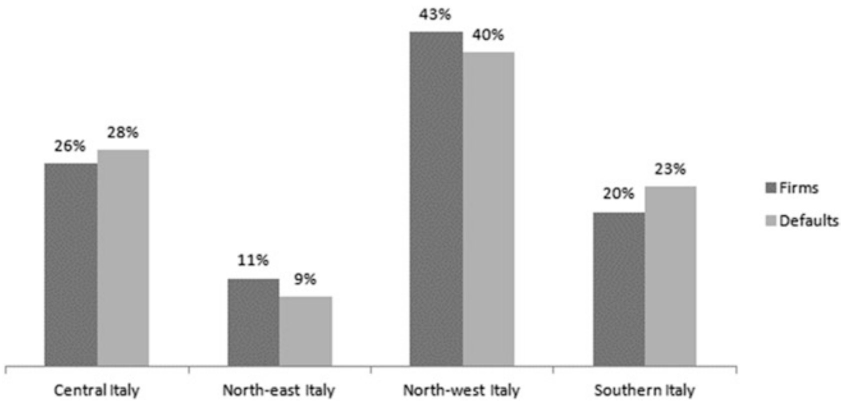

Fig. 5.4 Distribution of Italian defaults and firms by geographical area

- the correct identification of a hausbank relationship as opposed to a multi-banking relationship; and
- verifying the degree of consistency between balance sheet information and CCR information.

5.3 Model Architecture

The model estimates the PD over the 12 months following the moment a company's creditworthiness was assessed. It has a modular structure composed of three sub-modules:

(a) Hausbank Behavioral Module (or Leading Bank Behavioral Module) based on SME-bank data from the CCR;
(b) Multiple Banks Behavioral Module (or Non-Leading Banks Behavioral Module) based on the SME-aggregate non-leading banks data from the CCR;
(c) Financial Module based on financial statements data, with an approach similar to best international practice).

All sub-modules process three scores in a separate and parallel manner: these scores are calibrated and validated for the purpose of estimating the counterparty's PD. Through calibration, each score is turned into a PD which, on a scale from 0.03 % (lowest risk) to 20 % (maximum risk), reflects the probability that, during the 12 months following the analysis, the borrower will become insolvent, according to the adopted definition of default. These modular PDs are subsequently combined, on a weighted average basis, into a single PD.

As noted previously with regard to the behavioral modules, it is considered preferable to develop two distinct credit performance models based on the different behaviors observed in the banking system; this relates to banks that have a predominant relationship with a firm and banks that have a marginal position with the same firm. A banks that has a predominant relationship with a firm tends to provide greater support to that firm, given the bank's greater share in terms of loans granted and disbursed. Also, the bank can cover the credit lines that may be canceled by other banks with a more marginal position with the firm. A bank that has a marginal position with a usually carries out these transactions with a view to acquiring new customers; however, if the credit situation deteriorates they are more prone to classify the position (i.e. to classify the firm as being in a state of default according to the regulatory definition) and are less likely to reach negotiated settlements.

It follows that two distinct categories of banks, each reflecting substantially different commercial behavior, can be distinguished in the multiple banking relations usually held by domestic firms behavior: the leading bank(s) and the non-leading banks. For the purposes of modeling, a leading bank is that defined as the bank considered to be leading by the company's managers. In the absence of this indication, the single bank whose exposure to the firm in terms of the amount drawn down on a revocable facility/amount drawn down on revocable facilities with the banking system exceeds 40 % on the date the PD is calculated (i.e. the most recent CCR data). If two banks exceed this threshold, the leading bank is defined as the bank that has the highest ratio of the amount drawn down on revocable facility/amount drawn down on revocable facilities with the banking system.

5.3.1 Model Development

The model has been developed on the basis of the structured process shown in Fig. 5.5.

Step 1	Step 2	Step 3	Step 4	Step 5
Definitions, data collection and sampling	Univariate analysis	Multivariate analysis	Selection of the final model	Calibration and integration
- **Definition of default** - **Request for data** - **Data collection** - **Data Control** - **Distribution analysis** - **Construction of samples**	- Longlist - Expert opinion - Statistical testing - Factors transformation - Shortlist - Expert opinion	- Correlation and cluster analysis - Statistical regression - Check coverage of relevant categories - Identification of candidate modules - Expert opinion	- Modules testing - Expert opinion - Selection of best module by category	- AP estimate - Calibration - Modules integration - Breakdown analysis by class - Model testing - Expert opinion

Fig. 5.5 Development of each of the three modules

The various activities carried out in each step of module development are described in this book within the relevant chapters, which also describe their practical implementation.

According to published analysis, logistic regression is one of the best methods for estimating the function that associates the probability of a dichotomous attribute (in this case, bad = 1, good = 0) with a set of explanatory variables (financial, performance-based or qualitative).

The model has been developed on the basis of international best practices, which consider logistic regression as the best methodology for estimating the probability of default. Logistic regression is a special form of regression analysis where the dependent variable Y is dichotomous and has a binomial distribution, and the estimated Y, as it varies between 0 and 1, assumes the meaning of probability:

$$P\{Y = 1|x\} = \pi(\mathrm{x}) \text{ i.e.,}$$

$$Y = \begin{cases} 1, & \text{with probability } \pi(x) \\ x, & \text{with probability } 1 - \pi(x) \end{cases}$$

The logistic regression function appears as:

$$\text{logit } (\pi(x)) = \beta_0 + \sum_{i=1}^{n} \beta_i \cdot x_i = \mathbf{X} \cdot \beta$$

where logit ($\pi(x)$)denotes the natural logarithm of the ratio between the probability of success (i.e. the probability that the analyzed position becomes insolvent in the 12 months following the assessment) and the probability of failure (i.e. solvent), given the vector **x** of n predictor variables (e.g. performance data on the concerned position):

$$\text{logit } (\pi(x)) = \ln\left[\frac{\pi(\mathrm{x})}{1 - \pi(\mathrm{x})}\right]$$

Since $\pi(x)$ denotes the probability that Y has a value of 1 depending on the explanatory variables x, the probability of Y can be expressed as a logistic function:

$$\pi(\mathrm{x}) = \frac{\mathrm{e}^{X \cdot \beta}}{1 + \mathrm{e}^{X \cdot \beta}}$$

The logit chosen to describe the function that links the probability of Y to the combination of the predictor variables is based on the finding that the probability gradually approaches the limits 0 and 1, describing an S-shaped figure (called a "sigmoid"). While this is not the only function by which it is possible to model the probability of a given event, the logit is preferred over others because it represents a transformation of the ratio between two complementary probabilities (a quantity known as "odd"); that is, the number of successes for each failure of the event in question.

5.3.2 Development Samples

The baseline datasets for the development of the model consist of 21,770 firms in the SME segment, observed for five years up to December 31, 2007, and representative of the Italian economy both from a geographical and a sectoral perspective (see Fig. 5.6).

Each of the three modules has its own development sample.

The balanced development sample for the Financial Module consists of over 2200 enterprises; over 1100 were good enterprises and the remainder comprised bad enterprises (see Figs. 5.7, 5.8 and 5.9).

The balanced development sample for the Non-Leading Banks Behavioral Module consists of over 3000 enterprises; 1500 were good enterprises and the remainder comprised bad enterprises (see Figs. 5.10, 5.11 and 5.12).

The balanced development sample for the Leading Bank Behavioral Module consists of over 2100 enterprises; around 1000 were good enterprises and around 1000 were bad enterprises (see Figs. 5.13, 5.14 and 5.15).

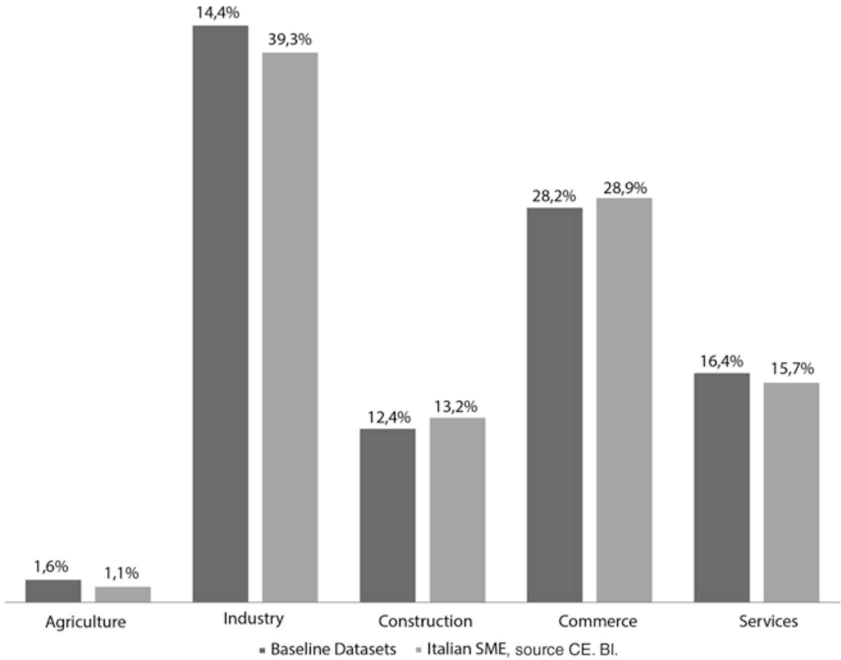

Fig. 5.6 Baseline datasets versus SME Italian distribution (Source: Capital investment research)

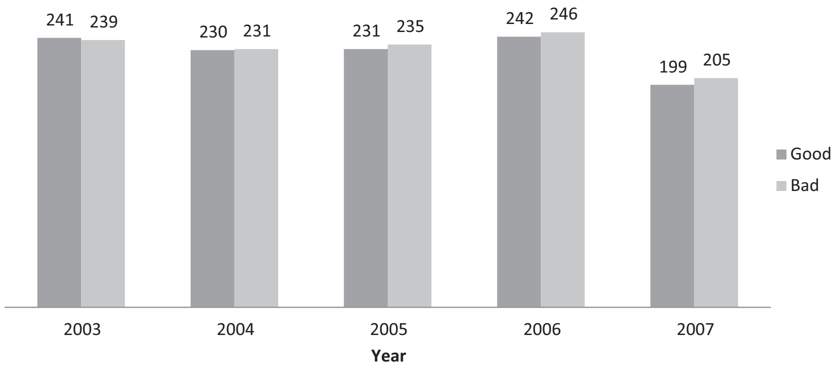

Fig. 5.7 Financial module development sample: good/bad time distribution

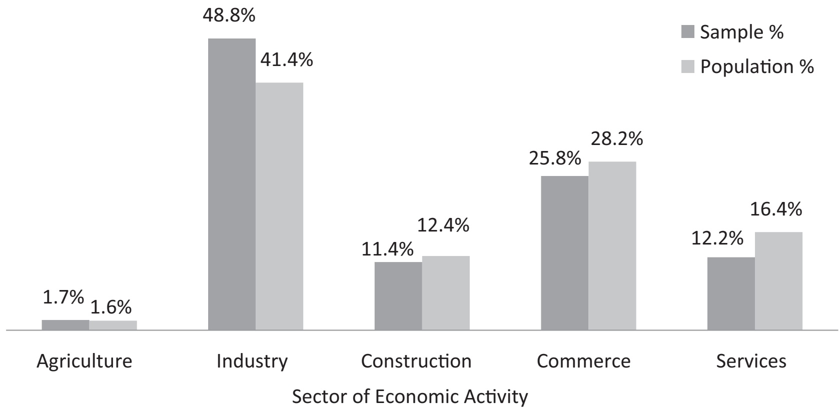

Fig. 5.8 Financial module development sample: industry distribution

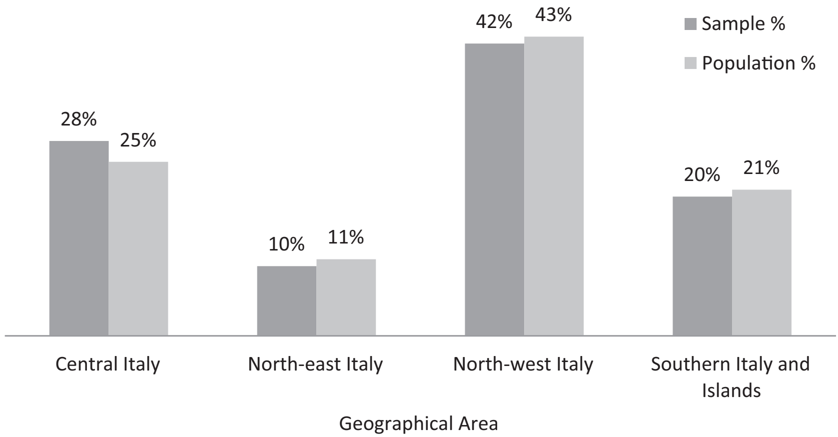

Fig. 5.9 Financial module development sample: industry distribution

The development samples for both the financial module and the behavioral modules were each built separately, in three steps:

Step 1 – Analysis of the reference portfolio;

Step 2 – Identification of the sample of bad firms and verification of their representativeness with respect to the economic activity and the geographical areas of all the identified insolvent positions;

Step 3 – Construction of the sample of good firms by adopting a random sampling methodology without replacement and stratified with

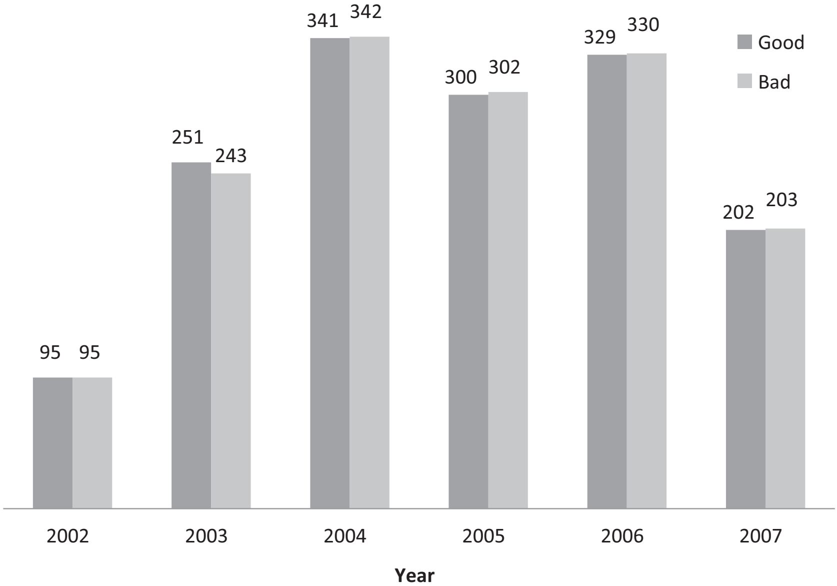

Fig. 5.10 Non-leading banks behavioral module development sample: good/bad time distribution

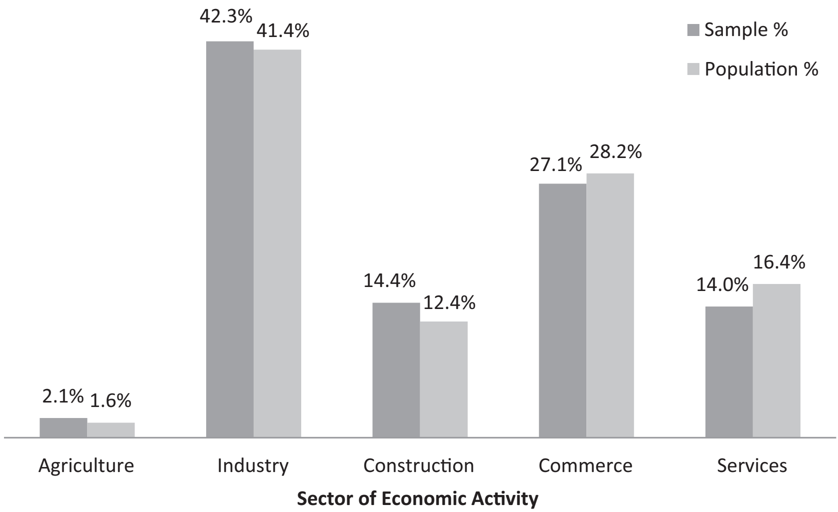

Fig. 5.11 Non-leading banks behavioral module development sample: industry distribution

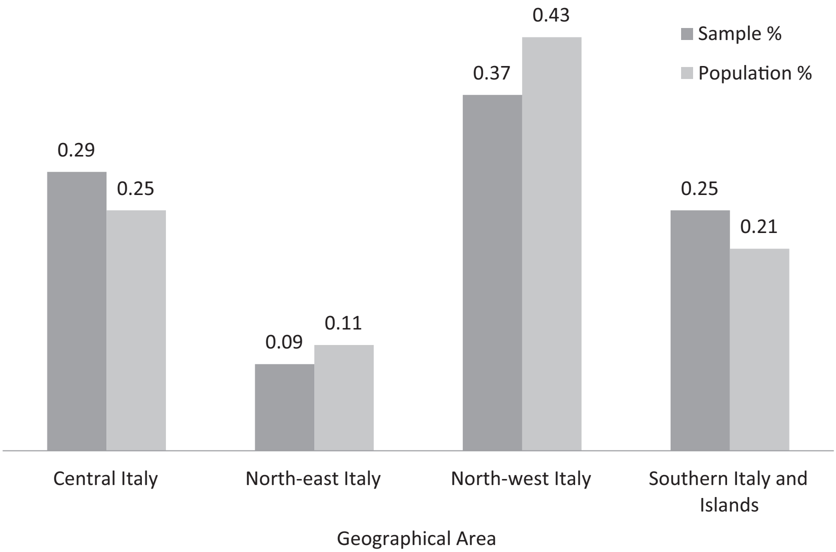

Fig. 5.12 Non-leading banks behavioral module development sample: geographical distribution

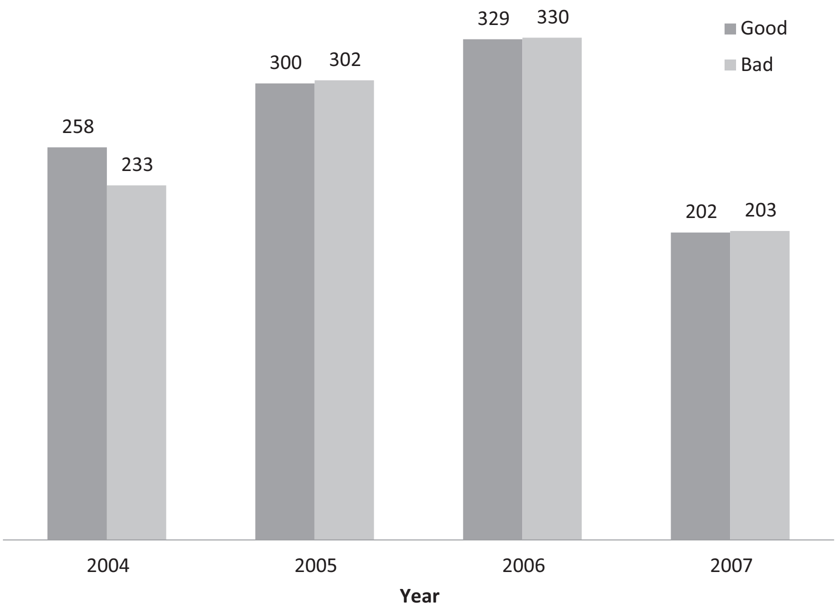

Fig. 5.13 Leading bank behavioral module development sample: good/bad time distribution

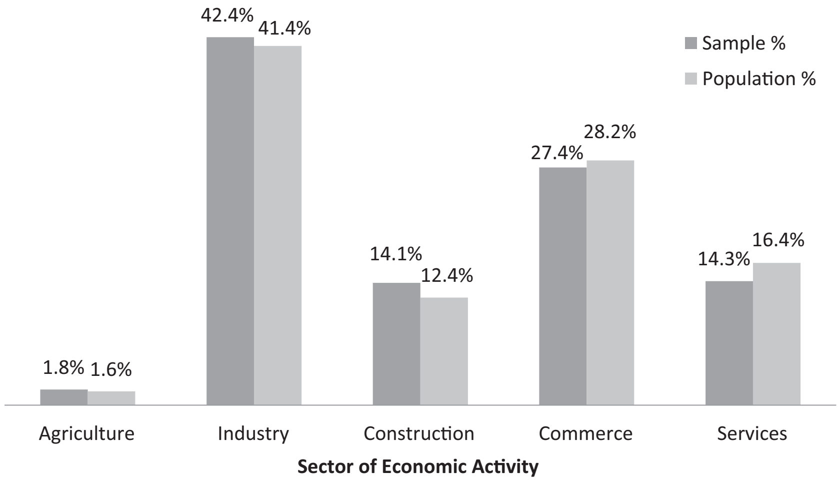

Fig. 5.14 Leading bank behavioral module development sample: industry distribution

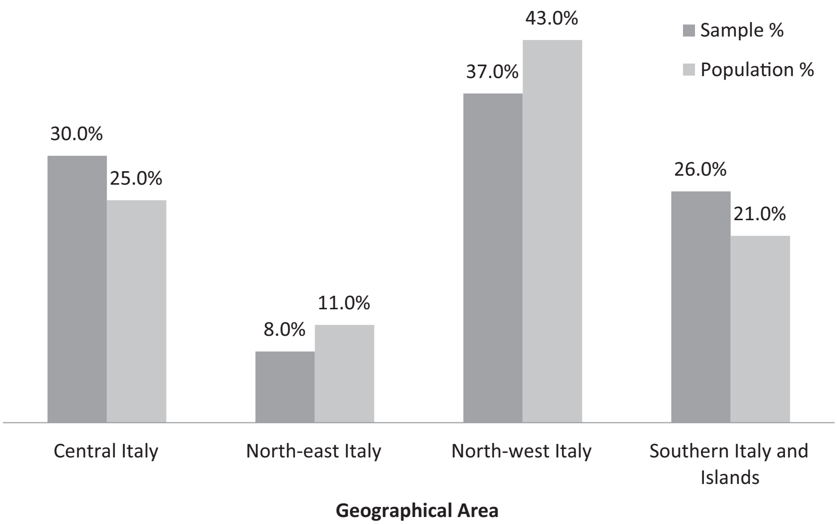

Fig. 5.15 Leading bank behavioral module development sample: geographical distribution

respect to the representativeness variables and the year of default, with constant sampling probability (simple sampling) across subgroups.

The sample thus obtained was tested to verify:

1. the completeness of the information;
2. compliance with the evidence identified in the population at December 31, 2007 (non-compliance with any of these conditions would have resulted in a new extraction of the sample).

The estimation samples of the Financial, Leading Bank and Non-leading Bank modules' financial, internal performance and external performance modules were tested for representativeness using the Population Stability Index (PSI).

Financial and CCR information was attributed to the positions within the SME estimation samples according to the criteria shown in Fig. 5.16.

If d indicates the time of default of a generic bad position, the data observation period for the (bad) position in question and the corresponding good position ranges from:

- d-12 to d-15 for the behavioral indicators – so that, for example, it is possible to build quarterly averages;
- d-19 to d-43 for the financial variables – in order to simulate the actual availability of the financial statements when applying the model.

Fig. 5.16 Behavioral data window versus financial data window

5.3.3 Univariate Analysis, Multivariate Analysis and Model Weights

This section describes the methodology used to identify the long list, the selection of the short list, the multivariate analysis for the definition of each sub-module and the final integrated model.

The first analysis, conducted separately on each factor in the long list, is aimed at identifying U-shaped relationships (that must also be confirmed by the financial analysis) between the range of values taken by the indicator and the default rate.

The analysis was carried out by breaking down the range of values of each variable into sub-intervals (more precisely, quantiles) with respect to which the observed default rate was calculated.

The median value of each sub-interval and the corresponding default rate were identified, respectively, on the X and Y axes of a Cartesian plane to obtain a graphic representation of the relationship of each indicator with the default rate.

Given the U-shaped pattern, and having fixed the point ($x0$; $y0$), where the sign of the first derivative of the underlying implicit function changes (ideally, the minimum point of a parabola facing upward), the best preliminary transformation (piecewise linear or quadratic) (defined as U) that could ensure vicinity to the point ($x0$; $y0$) and simultaneously minimize the mean square deviation between the interpolating curve and the observed values was identified.

At the end of the preliminary analysis, all factors in the long list were *monotonic* (increasing or decreasing, in terms of their financial meaning) with respect to default, leading to a more accurate assessment of their predictive ability.

The subsequent analysis conducted on the factors in the long list (preliminarily transformed by the U operator, where appropriate) was intended to identify, for each of them, the range of values [xl; xu] where:

- a significant portion of observations (at least 80 %) would fall; and, at the same time,
- the monotonic relationship with the default event proved to be particularly evident.

Once the extremes of this range, called the "upper" and "lower" bounds, respectively, and denoted as *x u* and *x* 1, were identified, the discriminating power of each factor within the [*xl*; *xu*] interval was enhanced (through a logistic (deterministic) transformation, L_d), while it was flattened outside the interval where the relationship with the default event was found to be less obvious.

In analytical terms, by defining the percentage of observations falling on the left-hand side of the interval as l (lower), the percentage falling on the right as 1 − u (u = upper) and the generic value included in the identified interval as *x*[*xl*; *xu*], the transformation of *x* is defined as:

$$L_d(x) = \frac{1}{1 + e^{-p\cdot(x-f)}}$$

where

$$= \frac{\text{logit}(u) - \text{logit}(l)}{x_u - x_l} = \frac{\ln\left(\frac{u}{1-u}\right) - \ln\left(\frac{l}{1-l}\right)}{x_u - x_l}$$

is the average slope of the curve in the interval [*xl*; *xu*] and

$$f = \frac{x_u + x_l}{2}$$

is its point of inflection, while for the values falling outside the interval [*xl*; *xu*], the following relations apply:

$$L_d(x) = \begin{cases} L(x_l), \text{if } x < x_l \\ L(x_u), \text{if } x < x_u \end{cases}$$

At the end of the transformation determined by the L_d operator, an analysis was carried out to assess the discriminatory power of the individual indicators, based on an evaluation of their accuracy ratio and the consistency of the ratios with respect to the economic meaning attributed to them, as well as the likelihood that the directors' discretion in the preparation of the financial statements might be precursory to any type of window-dressing practices.

As previously noted with regard to the Behavioral Modules, the development of two distinct credit performance models for predicting the PD was considered preferable: one based on a firm's bank account data with the leading bank and the other on the firm's aggregate data with non-leading banks.

The standardization and transformation of the CCR variables used for the Leading Bank Behavioral Module and Non-leading Banks Behavioral Module were thoroughly analyzed. The related long list consists of approximately 180 behavioral indicators, derived from the various types of exposure included in the Italian CCR, which were reprocessed to obtain absolute values, differences, ratios and min–max deviations.

On the basis of the indicators' ability to sort default events and economic meaning, a short list for each sub-module was defined.

With regard to the credit performance module, we have extracted the short list from the long list for both bank module types:

1. Leading Bank Behavioral Module (hausbank commercial relationship): 32 variables with high univariate accuracy ratios;
2. Non-leading Bank Behavioral Module (multiple bank commercial relationship): 22 variables with high univariate accuracy ratios.

Below are some examples these analyses:

The relationship between the average quarterly amount drawn down/revocable lines and credit commitments offers an evaluation of the extent to which an SME has used its overdraft facilities during the previous 12 months, in relation to the number of overdraft facilities it has obtained from all lenders, without differentiating self-liquidating credit lines. It is one of the indicators typically used to reveal the adequacy/sustainability of an SME's credit lines. The analysis yields an accuracy ratio of 47.1 % (see Fig. 5.17).

The relationship between the average quarterly amount drawn down on revocable facilities/revocable lines granted shows the quarterly average of an SME's usage of revocable overdraft facilities obtained from all lenders over the previous 12 months, and is the key indicator of the economic strength of the corporate treasury. The analysis yields an accuracy ratio of 63.2 % (Fig. 5.18).

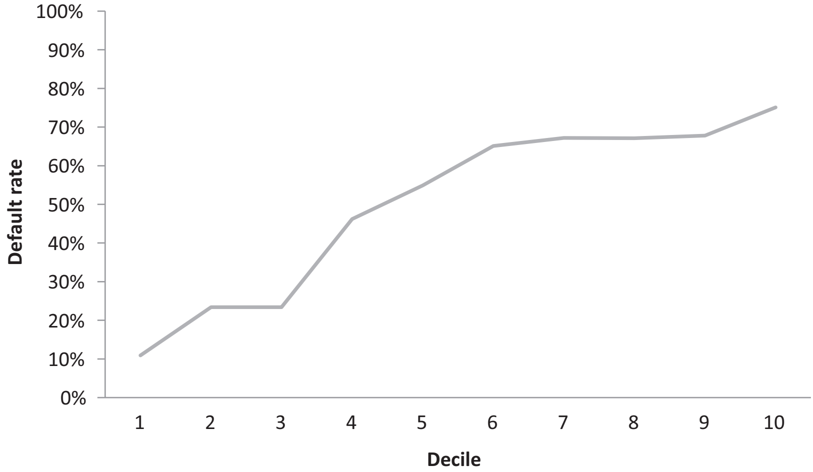

Fig. 5.17 Average quarterly amount drawn down/revocable lines and credit commitments

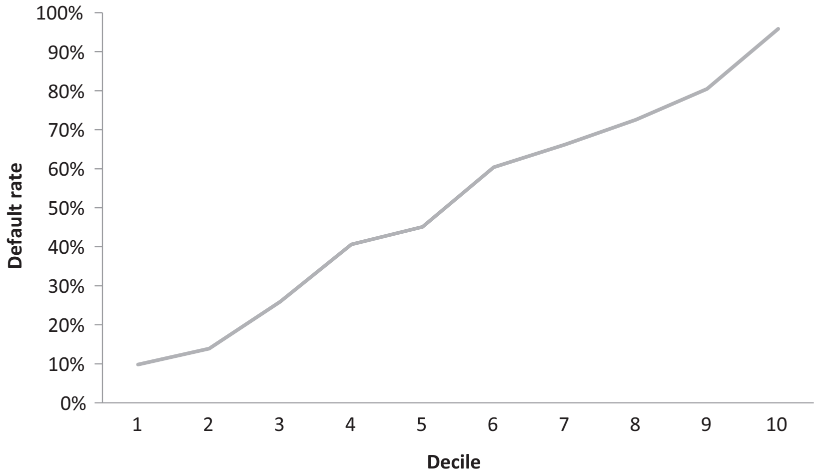

Fig. 5.18 Average quarterly amount drawn down on revocable facilities/ revocable lines granted

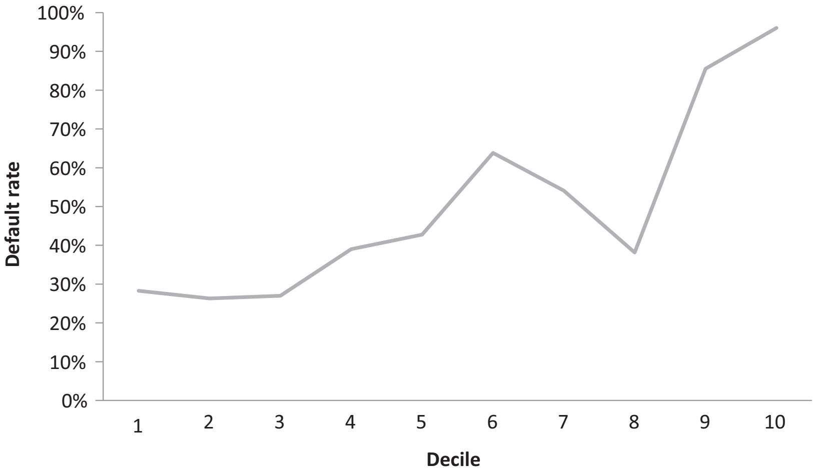

Fig. 5.19 Overdrawn exposure/revocable facilities and credit commitments

The overdrawn exposures on revocable facilities and credit commitments indicator shows a positive value where credit limits have been breached and is a point-in-time indicator of stress, or the absence thereof, affecting the SME's credit lines with the banking system. The analysis yields an accuracy ratio of 46.1 % (see Fig. 5.19).

The indicator of the maximum quarterly overdrawn exposures on revocable facilities/revocable facilities granted is intended to capture the maximum levels of overdrawn exposure on revocable facilities in relation to the total facilities granted during the previous 12 months, and allows an evaluation of the adequacy of the facilities themselves in relation to the cyclic nature and seasonality of the business. The analysis yields an accuracy ratio of 66.0 %. (Fig. 5.20)

The next step was a correlation analysis between the short-listed variables, a multivariate analysis and the selection of the sub-module considered as optimal.

The three modules show the following accuracy ratios in development samples on a stand-alone basis (in sample, excluding missing values). It will be seen later that the accuracy ratio of the overall model is much higher than the average accuracy ratio of each stand-alone module. The accuracy ratios of the three modules are:

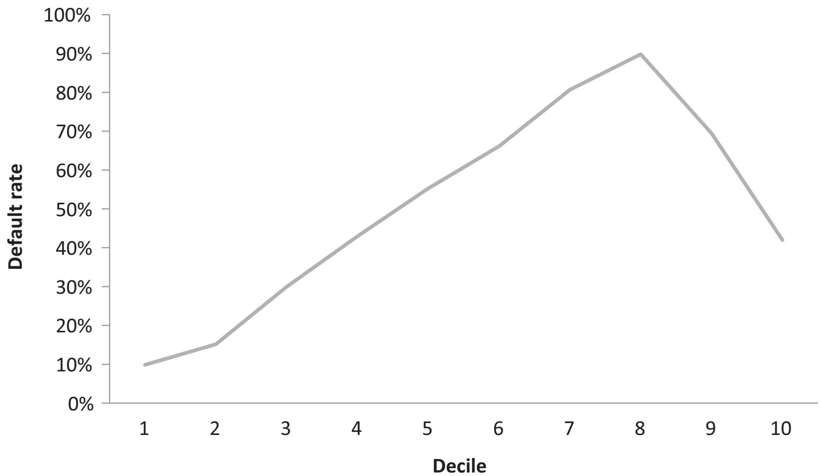

Fig. 5.20 Maximum quarterly overdrawn on revocable facilities/revocable lines granted

1. Accuracy ratio of Leading Bank Behavior Module = 69.7 %;
2. Accuracy ratio of aggregate Non-leading Banks Behavior Module = 69.9 %;
3. Accuracy ratio of Financial Module = 61.9 %.

5.3.4 Central Tendency

Estimates of long-run aggregate probabilities of default (or central default tendency) are an important issue, as they form an anchor point for the model. The default probabilities are calibrated in a 12-month horizon and an expert team supports the estimation of the anchor point year by year. In 2013–2014, the anchor point was 2.08 %.

5.4 Validation of the Model

The validation of the model was carried out on very large out-of-sample and out-of-time (2009–2012) datasets. Each module was validated individually and the Combined Model was validated as a whole. A summary

Table 5.1 Out-of-time and out-of-sample validation datasets

Sample	Performing positions at the beginning of period	Of which in default within the next 12 months	Default rate (%)	Accuracy ratio multi-year range (%)
Leading Bank Behavioral Module	64,221	929	1.45	57–60
Non-leading Banks Behavioral Module	77,327	1054	1.36	60–68
Financial Module	60,151	429	0.71	58–70
Combined Model (on single/intersection)	41,954	293	0.70	78–85

of out-of-sample and out-of-time datasets and accuracy ratios is reported in Table 5.1.

The Combined Model, which maximizes the overall accuracy ratio and ensures a good balance between the three modules, has the following weights:

1. Leading Bank Behavioral Module: 30 %;
2. Non-leading Bank Behavioral Module: 35 %;
3. Financial Module: 35 %.

The selection was made by reducing the following methodological aspects to common factors:

1. The results of simulations to determine the optimum accuracy ratio according to changes in the various weightings of the three modules;
2. The opinion of the group of experts called upon to carry out their qualitative evaluation of the balancing of the various modeling elements;
3. The desire to keep each module distinct and separate from the others in order to be able to work on each module individually in evaluating credit risk. With this approach, we preserved the richness of information obtained from reading the PDs derived from hausbank relationships separately from PDs derived from multi-engagement

relationships. In the same way, we preserved the richness of information obtained from contrasting PDs based on balance sheet data with PDs derived from CCR data. In doing so, however, we gave up the ability to optimize a collective accuracy ratio, which could have been obtained had the scores of each module been harmonized into a single score, and subjected to validation and calibration.

In order to verify the robustness of the model's accuracy ratio estimate, calculated on out-of-time and out-of-sample datasets, we proceeded to apply the Mann-Whitney test to establish the confidence interval.

The model's aggregate accuracy ratio is 81.4 %

The Combined Model accuracy ratio on the overall out-of-time and out-of-sample datasets is 81.4 % with a Mann-Whitney test confidence interval of 78.2 % (lower bound) and 84.6 % (upper bound).

The restricted interval of the accuracy ratio supports its validity.

5.5 Leveraging Behavioral Data and Enhancing Model Accuracy

SME credit rating models based on balance sheet information as well as behavioral information held in CCRs regarding bank–client relationships are proved to be highly predictive

While the accuracy ratios of each of these two approaches (financial and behavioral), if taken individually, falls between 66 % and 70 %, in the new approach the model's overall accuracy ratio reaches 80–84 %.

This result can be explained by the different role played in forecasting a state of insolvency by information from financial statements, as opposed to information based on credit performance.

With respect to SMEs, for which audited financial statements are not required, financial statement data:

(a) is by its very nature available on a delayed basis;
(b) is potentially subject to creative accounting practices;
(c) is provided on an annual basis.

In essence, financial statements are useful to estimate the probability of default over a period of 24–36-months following publication. However, they show little flexibility in capturing a situation of strained liquidity or overstretched credit lines vis-à-vis the banking system on an ongoing basis. This fact is especially relevant under the Basel regulations since default – before reaching pathological conditions such as those envisaged in banks' classifications in watch-listed or in non-performing loans, or those resulting in the cessation of business – is defined as credit lines overdrawn for an extended period of time (i.e. past-due).

Conversely, the information available in CCRs:

(a) is not subject to corporate practices of creative accounting;
(b) is available within a week;
(c) is updated on a monthly basis;
(d) has a stronger correlation with the past due definition of default;
(e) provides a reliable picture of an SME's liquidity situation.

In modeling CCR behavioral variables, it is important to take into consideration the different relationships between SMEs and banks according the two principal schemes: the hausbank (or leading bank) relationship and multiple bank relationships (aggregate non-leading banks).

This methodological choice resulted from the different behaviors observed in the banking system between banks that have a predominant relationship with a firm, compared with banks that have a marginal position with the same firm.

By combining the predictive ability of the financial statement approach with the predictive ability of the behavioral approach (in terms of a hausbank or multiple banks position), it is possible to achieve a synergistic effect in the overall accuracy ratio. The accuracy ratio improvement is in the region of 14 percentage points.

The higher accuracy ratio of the model under the new approach allows for the optimization of the predictions in EU systems, which are predominantly bank-centric, as evidenced by the IMF's Financial Stability Reports.

The new methodology leverages CCR data, follows a flexible approach and differentiates between the hausbank (leading bank) model and the multiple-bank (non-leading banks) model when evaluating the relationship between the bank and the SME. This mathematical flexibility is useful in applying the methodology in EU countries other than Italy.

5.6 Two SME Credit Risk Assessment Cases

In order to better explain the added value of CCR data compared with typical balance sheet data, two examples using real company data are offered.

5.6.1 Company A

Company A operates in the manufacturing sector with annual revenue of €8,320,000. On December 31, 2012, the company presented the following healthy balance sheet:

Net debt/EBITDA	4.8
Interest costs/EBIT	46 %
EBITDA/sales	4.3 %
Debt/equity	2.5

An evaluation of credit risk using a model based on balance sheet data gives an estimated 12-month expected default frequency of 0.35 %.

An examination of CCR data yields additional information, some positive and some negative; in particular:

1. Company A does not have a leading bank relationship, but works with four different credit institutions.
2. The ratio of credit reserve to credit used across all lenders contracted over the last three months went to 7.4 % from 12.9 %.
3. The safety margin associated with the use of revocable lines of credit contracted over the last three months went to –10.4 % from 200 %; also, the company breached its credit limits twice during the last two months. The company's treasury is consequently under pressure and is compelled to undertake the rapid regeneration of liquidity (i.e. by disposal of non-core assets, etc.).

An evaluation of credit risk using a model based on CCR data gives an estimated 12-month expected default frequency of 5.35 %, which is clearly in the elevated risk zone.

Based on a combined reading of balance sheet information and information on commercial relationships with the banks, the estimated credit risk is of the order of 3.1 %; that is, in the high-yield sector.

5.6.2 Company B

Company B operates in the food producing sector with annual revenue of €11,675,000. On December 31, 2012, the company presented the following relatively healthy balance sheet:

Net debt/EBITDA	6.3
Interest costs/EBIT	51 %
EBITDA/sales	7.8 %
Debt/equity	0.6

An evaluation of credit risk using a model based on balance sheet data gives an estimated 12-month expected default frequency of 0.61 %

An examination of CCR data yields additional positive information; in particular:

1. Company B has a leading bank relationship (in which 50 % of the drawn credit lines are concentrated) and also works with two other credit institutions.
2. The ratio of credit reserve to credit used across all lenders has remained constant during the last three months, at around the 160 % mark.
3. The safety margin associated with the use of revocable lines of credit has increased during the last three months, to 240 % from 200 %, with no credit limit breaches. The company's treasury position is consequently very good and an expansion of business activities may be envisaged.

An evaluation of credit risk using a model based on CCR data gives an estimated 12-month expected default frequency of 0.22 %, which is clearly in the low-risk zone.

Based on a combined reading of balance sheet information and information on commercial relationships with the banks, the estimated credit risk is of the order of 0.4 %; that is, at investment grade level.

The following are the main points of the new proposed methodology:

1. The capacity to transform CCR behavioral data from the commercial bank-SME relationship into a PD, in line with the regulatory definition of default (i.e., past-due with a 100 % danger rate);
2. The capacity to differentiate between commercial bank–SME relationships of a hausbank type and commercial bank-SME relationships of a multiple engagement type, thus producing different behavioral PDs (the algebra incorporates two different types of commercial behavior);
3. The capacity to exploit fully the synergies between financial models and behavioral models, resulting in the notably improved predictive capability of (an out-of-sample and out-of-time jump in accuracy ratio to 81 % from 68 %);
4. A modular and flexible approach which allows the new methodology to be extended in the 14 EU banking markets that offer CCRs (in all EU countries, SME funding is excessively bank-centered, according to the IMF's Financial Stability Reports) and potentially also in the 41 countries outside the EU that have a CCR system;
5. The "open architecture" by which the model can be further empowered through developing and inserting new behavioral modules based on SME energy consumption, on SME phone and data utilization, on SME web indexing and reputation, and so on. According to the writers, an upward or a downward "jump" in the IT or energy consumption is always linked to a "not-normal" situation that can be used in an "early warning" credit rating system in terms of accuracy ratio improvements.

5.7 SME Credit Risk: An Empirical Analysis

This section discusses the dynamics of the credit risk on a sample of 10,000 Italian SMEs studied in 2010–2014 (Source: Capital Investment Research on commercial bank databases). The analysis is based on the application of the model described in this chapter.

The crisis has had a significant effect in terms of bankruptcies, cessation of trading of companies and a rise in unemployment. The progressive reduction of bank credit led to a phenomenon of "polarization" and selection of SMEs: the best SMEs on one side, with high turnover abroad, mainly self-sufficient in economic and financial terms and on the others; on the other side were the SMEs experiencing financial difficulties. The top group of SMEs has a good internal rating grade and their loans present a low absorption of regulatory capital: therefore, the banking system has offered credit in abundance and low prices. The second group of SMEs progressively lost the support of the banking system.

In this perspective, the European Central Bank Long-Term Refinancing Operations (LTROs) and Targeted Long-Term Refinancing Operations (TLTROs) did not improve the health of SMEs. More precisely, banks mainly used LTROs to buy government bonds and profit from the spread between the cost of funding and the yield on government bonds. The final effect was that a very low level of funding reached the so-called "real economy". Banks used TLTROs according loans to SMEs with the best internal credit rating (lower bank capital absorption) and not used to fund SMEs with a lower internal credit rating (higher bank capital absorption): this bank selection contributed to the phenomenon of "bias/polarization" described above.

The reason for this behavior lies in the fact that LTRO-TLTRO operations solve a problem of bank liquidity and not a problem of bank capital. Under Basel Regulations, the allocation of credit is based on the allocation of capital: there is an abundance of credit only if there is abundance of bank capital; there is a reduction of credit if there is bank capital shortage.

In sum, the "bottleneck" that hampers the restarting of bank lending to SMEs is the shortage of bank capital and not a shortage of bank liquidity. The European Central Bank is taking two directions: increasing bank liquidity, in order to avoid any bank failure; and, at the same time, increasing bank capital requirements, thus discouraging lending to marginal firms.

Figures 5.21, 5.22, 5.23 and 5.24 illustrate the distribution of the probability of default of the Italian small and medium-sized enterprises in the years 2011–2014 (Source: Capital Investment Research on the BNL-BNP Paribas database).

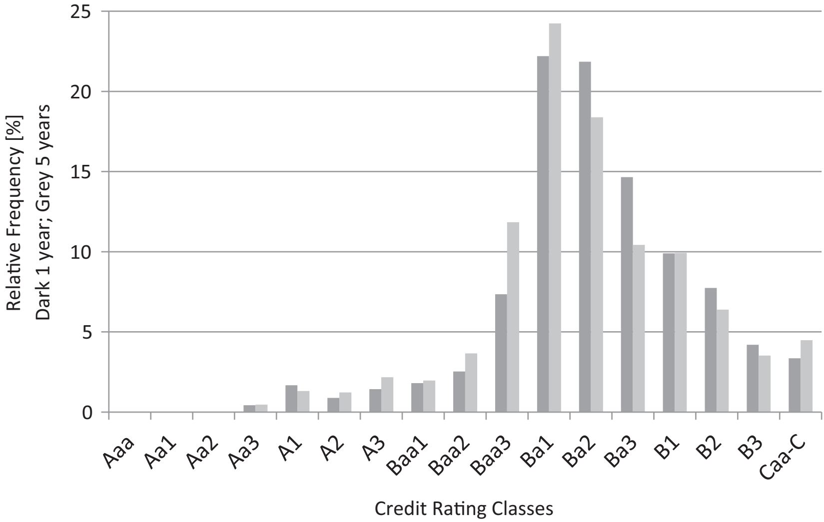

Fig. 5.21 Credit rating distribution 1–5 years, 2011

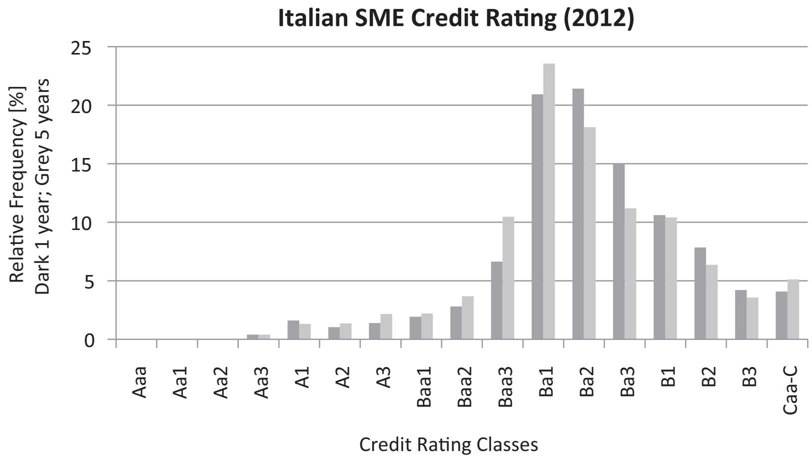

Fig. 5.22 Credit rating distribution 1–5 years, 2012

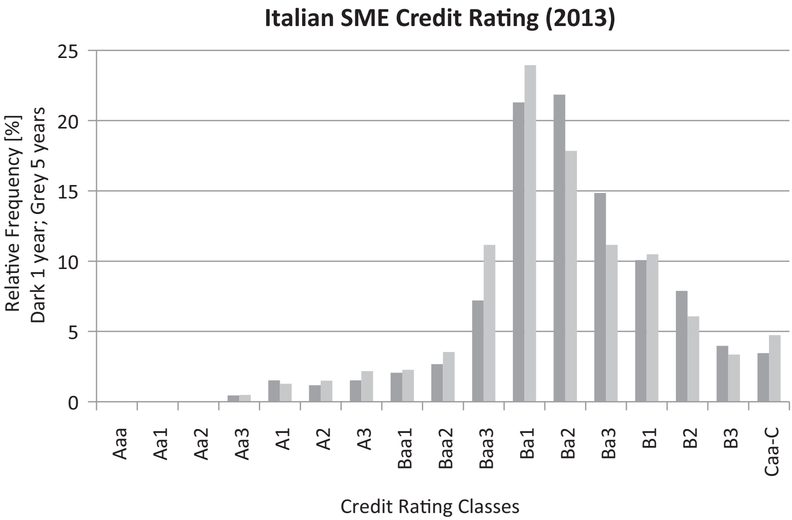

Fig. 5.23 Credit rating distribution 1–5 years, 2013

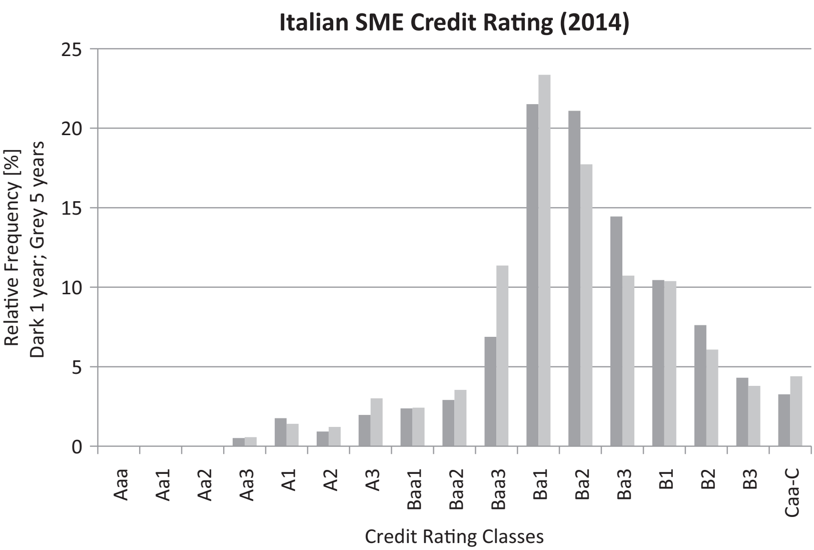

Fig. 5.24 Credit rating distribution 1–5 years, 2014

As you can see from the above figures, the percentage of Investment Grade companies remains very low, apart from the class Baa3. The larger classes are consistently Ba1, Ba2 and Ba3. It is also interesting to note that, in all the years examined, the 5-year probability of default tends to improve compared with the 12 month probability of default for classes Baa2, Baa3 and Ba1, while the 5-year probability of default tends to deteriorate compared with that at 12 months for classes Ba2 and Ba3. This gap can be read as a result of the "polarization" described above.