An Integrated Multi-model Credit Rating System for Private Firms

Giovanni Butera

Royal Melbourne Institute of Technology

Robert Faff*

Monash University

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The BIS 2001 opened the door to the possibility of using, subject to validation by the individual national supervisory authorities, systems of internal rating of credit risk developed by the banks when they satisfy certain criteria. Specifically, the Basel Committee proposed two approaches to the internal rating of credit risk – the 'foundation' and 'advanced' approaches. As such, there is a different degree of bank "autonomy" in the estimation of the parameters relevant to determining the risk weighting and thus to capital adequacy: there is lesser autonomy in the case of the 'foundation' approach and greater autonomy in the 'advanced' version. This paper presents a compound credit risk modelling approach for private firms which fulfil 2001 Basel Accord requirements in the case of the adoption of the foundation approach. We present findings from applying this model to a large sample of client firms of the Bank of Rome.

* Corresponding author: Department of Accounting and Finance, Monash University, PO Box 11E, Clayton Vic 3800, AUSTRALIA. Tel: +61 3 9905 2387; Fax: +61 3 9905 2339; Email: robert.faff@buseco.monash.edu.au

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1. Introduction

The use of credit rating models is a rapidly growing area of interest, not only in capital markets but also as an internal tool for banks, largely driven by the new Basel Accord on capital requirements. Indeed, in January 2001 the Basel Committee published a proposal to reform the methodology established in 1988 for the measurement of capital and the definition of capital standards for credit risk. The New Basel Capital Accord aims to develop a risk sensitive framework that contains a range of new options for measuring both credit and operational risk. Within this framework, a range of risk-sensitive options for addressing credit risk valuation begins with the standardised approach and extends to the "foundation" and "advanced" Internal Rating Based (IRB) approaches. These evolutionary approaches will motivate banks to continuously improve their risk management and measurement capabilities. Importantly, the key element of the revision contained in the new Basel Accord is to focus a greater emphasis on a bank's own assessment of the risk to which they are exposed in the calculation of regulatory capital charges.[1]

In general, a bank's internal measures of credit risk are based on assessments of borrower and transaction risk. Most banks base their rating methodology on borrower risk default and typically assign a borrower to a (credit) rating grade. A bank would then estimate the 'probability of default' (PD) – that is, the likelihood that the borrower will default within a year, associated with borrowers in each of these internal grades.[2] In addition to this measure, banks should also provide a measure of how much per unit of exposure they will lose should such an event occur – that is, the 'loss given default' (LGD). While many banks are able to produce robust measures of PD, far fewer banks are able to provide reliable estimates of LGD, due to data limitations and the bank specific nature of this risk component. It is for this reason that both the "foundation" and "advanced" IRB approaches have been proposed. In the former case, LGD values are set by supervisors' rules,[3] while in the latter approach, the bank will have the opportunity of estimating the LGD of an exposure, subject to meeting additional and more rigorous minimum requirements for LGD estimation.

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[1] Largely as a result of the recent Basel Committee activity, academic research efforts have expanded at a furious pace. For example, see Carey and Hrycay (2001); Krahnen and Weber (2001); Altman, Bharath and Saunders (2002); Benink and Wihlborg (2002); Bliss (2002).

[2] Generally speaking by 'default frequency' we mean the ratio of the number of defaulting companies over a given period of time and the population sample at the beginning of the period. When the number of observed cases tends to a very large number, that ratio can be considered a proxy of the probability of default. For this reason, in the text the terms 'default frequency' and 'probability of default' (PD) are used interchangeably.

[3] For example, exposures not secured by a recognised form of collateral will receive a fixed supervisory LGD depending on whether the transaction is senior or subordinated.

Many studies[4] have shown that having minimum required capital standards may improve banks' stability, but is likely to come at a cost in terms of operating in the banking business and thereby may lead to inefficiencies. In this view, it is advantageous to include a regulatory setting that encompasses a menu of different regulatory instruments other than regulatory standards, and banks are encouraged to develop their own internal model to assess credit risk exposure.

In the Credit Risk Model (CRM) literature it is possible identify three macro-approaches:

a) Models based on Merton (1977),[5] which utilize option theory (for example, *KMV*, JP Morgan *CreditMetrics*), and the probability of default depends on the volatility of stock prices. As a consequence, these models cannot be applied in economies where the number of listed companies is very small;

b) Models based on Wilson (1997) (*Credit Portfolio View* – known as a top-down model), based on the analysis of macro-economic factors and their influences on the probability of default of companies aggregated by sector and/or geographic area. The advantages of these models are the ability to precisely identify risk factors (so called *mapping*) and to forecast the probability of default as a function of different macroeconomic scenarios (*states of the world*).

c) Actuarial models (*Credit Risk*$^+$, Altman's (1968) *Z score* – known as a bottom-up model), where companies are partitioned into classes in relation to their rating and, successively, the frequencies of default on an historical basis for each class are estimated. When the number of companies analysed is very large, these frequencies can be considered a good approximation of the probability of default.

Many European markets (for example, Italy) are different from the US market because they are characterised by a very large number of non-listed small and medium size companies. This different market structure has profound implications on the way banks can assess the riskiness of their credit portfolio. Specifically, in these markets credit risk cannot be easily evaluated using either of the first two methods – applying ratings supplied by rating-agencies such as Moodys and Standard & Poors, or applying a Merton-type model to evaluate a credit position come with considerable difficulty. As a consequence, given the power of the Basel proposal, many European banks have inevitably been pushed towards the implementation of internal models for the assessment of credit risk following an actuarial setting.

The *bottom-up* type philosophy underlying the actuarial approach is characterised by five main phases.

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[4] See Basel Committee on Banking Supervision, Working Paper on the IRB Treatment of Expected Losses and Future Margin Income, BIS, July 2001.

[5] Also see J.P.Morgan, CreditMetrics™, Technical Documentation, 1997.

1) Selection of a representative company-clients sample, divided into healthy and defaulted clients. This represents the most delicate phase, and this topic will be addressed in section 3.
2) Defining balance-sheet and profit and loss indicators, which potentially can help explain the default of a company-client.
3) Computing the indicators and implementing a univariate analysis so to find out which of the indicators analysed are effectively able to discriminate between healthy and defaulted companies.
4) The information coming from significant balance sheet and profit and loss indicators in the previous step are then combined in a multivariate setting.
5) Testing the validity of the results obtained by the model using back test in-sample, out-of-sample, in-time, out-of-time, and external validation of the results.[6]

A crucial input into this approach to credit risk modelling is the accounting data and variables coming from the profit and loss statement and the balance sheet – the reliability of this raw data will considerably determine the quality of the risk assessment procedure. Unfortunately, we know that companies do manipulate their reported financials. Much empirical research carried our in US has supported various behavioural hypotheses of management adoption of accounting policies.[7] Specifically, these studies have shown that: (1) managers have a propensity to reduce earnings fluctuations (known as the 'income smoothing' hypothesis); (2) in the case of highly-levered companies, managers tend to adopt policies that allow them to avoid reporting deteriorating financial leverage ('debt-equity' hypothesis), and (3) managers tend to manipulate earnings when non-standard activities are planned within the next few months (for example, IPOs and Buy-backs).

In the current paper we extend and improve upon the bottom-up style of credit risk modelling and utilize a large sample of private company clients from the Bank of Rome to test the model. An important aspect of this analysis is that we take into account the manipulation of accounting policies and techniques ('creative' accounting) typically adopted by managers who lead Italian small and medium size companies. In some cases such manipulations are due to the peculiar and specific market microstructure which characterises the southern European region. We test the accounting manipulation hypotheses listed in the previous paragraph in the Italian market and

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6 Typically, an external validation of the results involves a comparison between the results obtained by a credit risk model and commercial indicators of the riskiness of companies, such a Dun & Bradstreet 'Failure score' and 'Delinquency score', Moody's Risk Calc for Private Firms and KMV Credit Monitor. Even though some of these indicators (like D&B scores) refer to the company riskiness of bankruptcy or commercial insolvency, and therefore have different objectives compared to a credit model aimed to assess the loans' credit risk, they can be considered a reasonable external setting to test the ability of the model to discriminate between "good" and ""bad" companies.

7 See for example, Burgstahler and Dichev (1997), Hall and Stammerjohan (1997), Griffiths (1986), Jameson (1988) and Naser (1993).

discover that creative accounting methodologies are more frequently used when the economy is in a recession phase than in the case of a recovering economy. This is important information in our analysis because the diffusion of creative accounting techniques during recession periods imposes a limitation on the information conveyed by balance-sheet indicators.

Another challenging aspect of the modelling approach concerns the issue of rating consistency. Indeed, initial tests of the difference in default rates of companies with equal rating but belonging to different industry sectors and geographic areas were highly significant. Interestingly, this analysis ignored macroeconomic and sector shocks. When the effects of these shocks are considered, however, the differences are no longer statistically significant. Motivated by this finding, we decided to enrich the model by introducing a correction to the estimated probability of default by incorporating a top-down analysis to allow our model to address this phenomenon. In so doing we develop a 'compound' credit risk model or integrated multi model credit rating system. Specifically, we explore two alternative ways to do so: the first, adopting a multi-factor approach; the second, applying a methodology similar to the Merrill Lynch investment clock for portfolio management.

In summary, the major aims of the present work are:

(1) To develop a compound credit risk model for private firms comprised of two sub-models, the approaches of which differ in terms of dataset construction, the way balance sheets and P/L information is aggregated, and therefore the results obtained.

(2) To devise a way to correct the historical PD produced by the bottom-up approach by transforming the results into a prospective PD using a top-down approach (by taking into account the influence of macro-economic variables on the probability of default of each economic sector).

(3) To incorporate the potential impact of 'creative' accounting techniques on the credit model predictions. Specifically, we will test whether the analysis of balance sheet policies adopted by managers improves the ability to predict companies' probability of experiencing a "bad" state.

The remainder of the paper is organised as follows. The next section will describe the data set utilised, starting from the definition of default used in the present analysis[8]. Furthermore, we will present two modes of analysis. In section 3 we present an illustration of the guidelines for the selection of a set of balance sheet indicators to be used in the construction of the model. Section 4 presents the two methodologies underlying the bottom-up approaches which, together with the top-

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[8] The definition of default adopted in the present work was originally suggested by the Italian Banking Association in "Methodological aspects of the implementation of a System of Internal Rating", Rome, November 2000.

down correction approaches proposed in section 5, are the engine of the integrated multi-model credit rating system. An examination of the effective advantages which its use brings compared to the use of a single approach model (either a top-down or bottom-up) concludes the section. The results of the evaluations and the various measures of the models' goodness of fit will be considered in section 6, with a detailed description of the validation processes and results obtained for the performance of the model. Furthermore, to address the recommendations of the Basel Commission, a procedure is proposed for regrouping, on the basis of the evaluations of default probability, the individual debtors in homogenous classes of risk. The results of such a procedure will furnish, finally, the fundamental input for the evaluation of risk-adjusted pricing system insomuch as it concerns the expected loss component.

2. Dataset Construction Methodologies

2.1. Definition of Default

The elements (statistical units), on which the predictive relationships are assessed, are the perceptible transitions in the available sample from a 'performing' loan to loan that is in 'default'. For present purposes, the model is designed to predict the onset of default remembering that each year the subjects exposed to the risk of experiencing default constitute all possible transitions. To that end, the model must assess the probability of transition of these risk-exposed subjects to a state of default, on the basis of the relationships observed between the effective transitions and the possible transitions.

In this work reference is made to a notion of default that is not limited only to those clients who enter into a state of default, but includes those who enter into a state of a doubtful loan. Motivating this choice is, essentially, the presumption that by considering all the difficulties a creditor might encounter, there would be a clearer assessment of the connections between the economic situation of the individual and credit risk, consequently increasing the predictive capabilities of the model. In addition, in adopting broader definitions, it is possible to have a greater number of observations of incidents of default, lessening the statistical problems connected with the assessment of rare incidents.

The choice of this definition of default finds accord with the most recent intentions of the Associazione Bancaria Italiana (ABI)[9] and, tangentially, with those of the Basel Committee. In defining the most adequate concept of default, the latter proposes: "occurring 'early' in the process of a borrower's deterioration", a definition which, in practice, might in the end be even 'earlier' than that adopted in this work. The particular definition of default adopted requires that, in every period, even the clients who have already fallen into doubtful loans be considered subject to the risk of deterioration. In fact, since the status of doubtful loan must be considered by the bank each period, it is regarded as opportune to use, as a unit of assessment, all the transitions that have given rise to a negative evaluation by the bank.

Summarising, all possible transitions will be defined from the sum of clients who in the initial period were solvent. The transitions into default will be determined from the sum of the same clients who at the end of the period ended up in default or doubtful loan. The probability of default will equal the relationship between the two.

2.2 Data and Dataset Construction Procedures

At this stage it is important to highlight that in performing any statistical, actuarial or econometric analysis the quality of the data and information used is crucial to obtain a meaningful result. It is also essential to understand the importance of the method used in assembling the information before using it. Indeed, the results coming from any analysis can be interpreted differently and therefore they can have different meaning, in line with the different methodology used to build the dataset.

The data used in this study can be divided in microeconomic data and macroeconomic data. The sources also can be divided into internal and external sources.

The microeconomic data is comprised of:

(A) Data regarding balance sheets and profit and loss indicators of about 30,000 small and medium sized Italian companies (with total sales between € 1 mil and € 250 mil); the sources of the data are both internal - Bank of Rome Marketing and Credit Department - and external - Ce.Bi and Boreau van Dik.[10]

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[9] Associazione Bancaria Italiana, "Methodological aspects of the implementation of a System of Internal Rating" (November 2000). The document, in justifying the adoption of a broad definition coinciding with that presented here, makes explicit reference to the advantage of observing a greater number of anomalous positions and to the greater efficiency of a managerial system based such an analysis of insolvency.

[10] CE.BI and Boreau Van Dik are two data service providers specialised in collecting balance sheet and profit & loss statements. While CE.BI is the result of a private consortium of Italian banks and its databases are for banks exclusive use, Bureau Van Dik is a publicly available database which collects balance sheets directly from the Italian Chamber of Commerce and Industry network.

(B) Data regarding the event and date of default for those companies which have experienced such a state during the observation period (1994-2001); the source is Bank of Rome Credit and Recovery Department.

The macroeconomic data is comprised of:

1) Yearly series of Italian GDP, inflation, short and long term interest rates, unemployment, consumption, and
2) Yearly series of the mortality rate and default rate frequency of the Italian Banking System partitioned into economic sector and type of borrowers.

The time period for the data covers 1984-2001 and the source is the Bank of Italy Statistical Bulletin.

As anticipated in the introduction, we present two alternative approaches of modelling credit risk in a bottom-up setting, namely the 'RANK' model and the 'LOGIT' model.[11] The RANK model is based on a dataset comprising 10,280 companies; we look at companies' balance-sheets in 1994, observe them for the following seven years, and during this period there are 1012 transitions to default (9.9%). The full yearly evolution of these defaults is displayed in Table 1. Hence the sample used is representative of the real distribution of default in the Italian banking system for that period (respectively ~10% transitions to default and 90% permanently solvent).[12] The transitions are evaluated taking into account the client's situation between the beginning and end of each period of the seven year of reference 1995-2001. Therefore, in the RANK model reference is made to the 1994 balance-sheet information for the entire credit portfolio set. Then, each year some of the companies included in the data sample go into default, and at the end of the period of analysis the starting dataset can be divided into two categories: performing and non-performing loans. The number of credit positions in default at the end of the observation-period divided by the number of credit positions observed in 1994 is calibrated to the 7-year cumulative frequency of default for the Italian banking System for the period 1995-2001.

[TABLE 1 ABOUT HERE]

While the dataset underlying the RANK model has been constructed in an actuarial setting, i.e. looking at the borrower at a given point in time and credit portfolio at a given date and then we follow its evolution in the coming years, in the LOGIT (logistic) model we start by looking at the

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[11] In our analysis, while the two different approaches bok at the same phenomenon, because this is done from a different perspective, they lead to different output, i.e. 1-year and 5-year PD. However, it is possible to transform them so as to obtain comparable results. This issue will be addressed in the next section.

[12] Therefore, we are not considering a balanced context (50% of observations in default and 50% solvent). Consequently, the results of the analysis will not need to be corrected to readjust them to the client base composition of the population in-default and performing companies.

companies in default each year during the observation period. Specifically, based on the defaulting companies for each year under observation and the default frequency of the Italian Banking System we estimate the number of performing companies per year to use in the analysis. The number of performing credit positions in the sample data, therefore, is chosen on the basis of the default probability at system level for each year. Furthermore, in the LOGIT model, reference is made to the balance sheet information of at least one and up to two financial years prior to the year in which the default is assessed. More precisely, if the default event happens during the first half of the year, reference is made to the balance sheet of the defaulting company over the two years prior to the event. In those cases where the default event occurs during the second half of the year, reference is made to just the previous year's balance sheet.[13]

The strategy adopted in this case for estimating default probability is based on the analysis of annual transition, for each of the seven years in the period of analysis, from a state of potential risk to an effective state of default. Thus the same client could be inserted more than once as a subject exposed to risk and therefore inserted as different observation, in subsequent periods, in the process of estimation/assessment. Only clients who have passed into default will be eliminated from the sample for the years subsequent to the event.

The principle underlying this approach is based on the decision to include in the evaluation all the transitions, over a given period of time, observable from the available data. In every period, the observation of the relationship between the change of state and the trend of the explanatory variables used in the model constitute an informative element which contributes to the total estimation. The resulting strategy of estimation is based on "pooled" data, such that every "possible transition" event is taken into consideration for the estimation. Every client (not in default) is included in the estimation as a valid observation for all seven years examined.[14] The advantage of such a dataset construction methodology rests on the fact that the output of the model consists of an annual PD, while in the RANK model we get a 7-year cumulative PD which then needs to be transformed into the corresponding annual PD.

From a different perspective, the advantages of using the dataset built for the RANK model is the ability to take into account some information that otherwise would not be captured. For example, a company with a return on equity (ROE) = 20% in 1994 may default in 1999. The

[13] The decision on which balance sheet to take into account to run the analysis is purely based on the fact that if a default occurs in the first half of the year, it would be meaningless tho take the previous year balance sheet for at least two reasons: (1) the balance sheet may not be available because generally it is made public in May of the next financial year; (2) it may be compiled after the event of default occurred.

[14] The use of data in "panel" structure, or rather of observations traceable to the same individual over diverse periods, permits the arrangement of a greater quantity of information with respect to cross-section analyses. The methodological approach pursued in this work exploits the "longitudinal" information making reference to the transitions of single clients. The presence in the sample of many transitions relating to the same subject creates potential for further methodological refinement of the model.

"present value" of this information is captured by the RANK model, while it would not be captured by a model which makes reference to balance sheet information coming from 1-year prior to default (i.e. dataset LOGIT model)

To complete the analysis we provide a correction of the PD due to the specific outlook on the economic cycle. This correction will also allow us to transform the historical PD obtained with a bottom-up approach into a prospective PD, that is an estimation of the PD which considers additional information on the economic outlook for the next year. The multi-period, multi-model approach, conjointly with the incorporation of a correction for the influence of next year's economic outlook on the PD potentially strengthens the model, offering the possibility of a predictive model's application for periods subsequent to those examined within the sample.

Therefore, "environmental" effects were assessed, relating to specific behaviour in the risk of homogenous groups of clients (in the form of sectors of economic activity, length of the relationship with the bank, geographic area and so on) on the basis of elements of semi-specific risk. Figure 1 describes the entire process: step 1 combines the results coming from the RANK and LOGIT models (bottom-up approaches), step 2 involves the correction for the macro-economic outlook (top-down approach) and step 3 adjusts for the length of the relationship between the bank and client.

[FIGURE 1 ABOUT HERE]

3. Illustration of Guidelines for Selection of Balance Sheet Indicators

In the corporate finance literature it is possible to list over a hundred financial ratios, many more than anyone has time to analyse systematically. This highlights the main problem of using financial ratios in the current setting: there are far too many of them which potentially can be used to explain financial distress. Therefore, one must find an efficient way to achieve the 'optimal' subset.

The most intuitive way to implement such a process is to initially examine each individual ratio in a univariate setting and then analyse the discriminatory power (between "good" and "bad" companies) of each individual ratio. The approach we adopted involved the following steps:

1) We started with the subjective opinion of corporate finance experts and credit analysts to identify a set of 35 balance sheets and profit and loss indicators.
2) We calculated these indicators for both datasets, for the RANK and LOGIT models.
3) For each ratio a univariate analysis is performed and values coming from each model are ranked in ascending order and then partitioned into deciles.

4) The number of defaulting companies for each decile are observed, and the ratios which produce a monotonic shape are chosen.[15] Three examples are provided in Figures 2a – 2c, for size, leverage and return on investment (ROI), respectively.
5) Finally, as a result of the above-mentioned process, a maximum of 11 ratios are assessed to have a significant discriminatory power amongst the two sub-samples of performing and defaulting clients.

[FIGURES 2a-2c ABOUT HERE]

The initial variable selection process described above, finds the most 'powerful' ratios that reflect the most obvious risk factors in four major areas: profitability, leverage, firm size and liquidity. Then, subsequently we add ratios and see if they add statistical significance to the group.[16] Usually, the more powerful risk factor ratio, such as income/assets, when used with a similar, correlated measure, such as Return on Equity, will generate coefficients where the most powerful ratio has a positive coefficient and the less powerful ratio has a negative coefficient, given the high level of correlation amongst factors. We do not use the additional ratio if it is statistically insignificant or it contains a "wrong sign". This is the stepwise process of variable selection: suggested by the univariate power and validated by a multivariate context.[17] The complete set of indicators, with the overall structure of the model are presented in Figure 3.[18]

[FIGURE 3 ABOUT HERE]

4. Integrated Multi-model Credit Rating System

4.1 Background

Historically, the first attempts at evaluating credit risk, going back to the 1960s, were based substantially on analysis of the influence individual indicators have on the risk of insolvency (univariate models). In the view of such analyses, the observation of significant differentiation in one indicator between healthy and defaulted companies should signal an indication of the probability of default.[19] The principal problems with this approach lie in the failure to consider the concomitant effects relating to the balance sheet indicators considered. The extension of the

[15] The liquidity ratio presents one exception – in line with expectations, it displays a U shape and is retained in the final set of ratios.
[16] A similar selection process has been adopted in Moody's Investor Service, RiskCalc™ Private Model: Moody's Default Model for Private Firms, New York, pag.28, May, 2001.
[17] Moody's Investor Service, Op. Cit., pag.29.
[18] All explanatory variables are normalised for SIZE (total sales), which is included as a separate factor (Small business: up to € 2.5mil; middle market: between € 2,5 and € 200 mil; large corporate: over € 200 mil.). This is because the profitability is obvious different depending on whether one is analysis a multinational conglomerate or a small and local company.
[19] See for example, Damodaran (1999).

univariate analysis to a multivariate setting allows us to consider not just one but a set of informative variables, all individually powerful but not perfectly correlated.

In the first phase of development of the multivariate approach, the discriminant analysis was broadly used. [20] This procedure of statistical classification permits, on the basis of a set of predictors, the classification of units according to the degree of risk on a quantitative scale (score). The subsequent choice of an appropriate "cut-off" point of separation, thus allows the classification of the units into two groups (those that are 'at risk' and those that are not at risk of default). Technically the discriminant analysis proceeds to the determination of an indicator (score), obtained as a linear (or quadratic) combination of the predictors. The coefficients of the combination are chosen in such a way as to maximise the distance between the averages of the indicator between the solvent unit groups and those in default. The optimal result for a discriminant analysis is achieved when a point exists for which the units in default have an inferior score and those in solvency have a superior score, or vice versa. If this does not occur, two types of classification error are committed. The first type consists of the percentage of subjects in default classified by the model as solvent, while the second type is the percentage of solvent subjects classified as in default.

To take into consideration the economic importance of these errors of classification, the determination of the cut-off point depends on the assumed loss function associated with the error. In general a higher cost is associated with an error which causes a company to be classified as healthy when it is actually destined to default (inasmuch as there is a loss, complete or partial, of the capital lent). In the converse situation, the opportunity cost of refusing credit to a healthy company (which is incorrectly classified as in default) is significantly inferior. The valid application of the discriminant analysis is constrained by a few basic assumptions: the distributional assumption requires the multi-normality of the variables involved, while for the applicability of the linear discriminant analysis, equality is required of the matrix's variance and covariance within the groups (solvent and default). Such an hypothesis is removed in the quadratic discriminant analysis.

In recent years, the use of multivariate regression models based on the logistical transformation (logistic regression) has gained favour as an alternative to the discriminant analysis.[21] The use of a logistic regression model allows us to synthesize in a mathematical formula the process of assigning a probability of default to a borrower. In addition, and compared to the discriminant analysis, the logistic model does not require the assumption of multi-normality of the

[20] Altman (1968) represents the pioneering study.
[21] See for example, Keasey and Mc Guinness (1990).

data. Often the strongly restrictive nature of that assumption alone prompts the use of the logistic regression model.[22]

However, in analysing the various options available in putting together the univariate information, one should also keep in mind how important it is to find a simple, intuitive (and powerful) way that is easily understood by the top-management of a financial institution, who often do not have any specific knowledge of statistical techniques. The RANK model relies in a simple way on the information coming from the univariate analyses performed on each indicator.

While it is a major challenge to find a suitable way to synthesise the information obtained from the borrower's balance sheet to estimate the probability that a borrower will default during the coming year, there are other difficult issues which need to be addressed. For example, (1) to find a multivariate modelling technique which is harmonised with the dataset construction methodology and, (2) to make the modelling decision about the variable used for estimation and the transformation of those independent variables. The former issue has been rarely addressed, if ever, by empirical research or academic literature on credit risk modelling, while the importance of the latter has often been underestimated.

We propose a compound credit risk modelling technique to address the issue regarding the harmonisation between the dataset construction methodology and the functional form of the models proposed. Furthermore, the variable selection process adopted here is essentially a step-forward procedure which starts with the most powerful univariate predictors of default, and we build upon the most powerful univariate information weighting not the ratios themselves but their corresponding default frequencies.[23]

4.2 RANK Model

The procedure used to calculate the PD using the RANK model, is based on a nonparametric approach and uses the rank of the numbers and the frequency of default associated to these numbers instead of the numbers themselves.[24] The steps followed to calculate the PD associated to each borrower using the RANK approach are:

1) Perform a univariate analysis for each indicator, by ranking them in ascending order, partitioning the series into deciles and then compute the default frequency of each decile.

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[22] The choice of the logistic model is motivated by elements which make it more versatile than the discriminant model: the logistic regression provides, in the case in which the sample structure reflects the population, the estimated probability, individual by individual, of the transition to default. Such a precious output would be useful for the implementation of credit-pricing related strategies, loans securitisation, etc.

[23] A similar approach was adopted by Falkenstein (2001), who addresses the non linearity feature of the ratios and the fact that these are sometimes not monotonically related to default adopting a nonparametric approach.

[24] See Birkes and Yadolah (1993) who illustrate many nonparametric procedures which are based on using the rank of numbers instead of the numbers themselves.

2) Rank the deciles in an ascending order in relation to the PD associated to each, and assign each decile the corresponding rank level (r_i).
3) Calculate a score for each company on the basis of the following formula:

$$Score = \frac{\sum r_i \times PD_i}{\sum PD_i} \qquad 1 < \text{score} < 10 \qquad (1)$$

This formula calculates for each company a score which is given by an average of the rank associated to each indicator, weighted by the PD associated to each rank.

4) Order the entire dataset on the basis of the score assigned to each company-client, dividing the score in deciles and calculate the frequency of defaults for each decile. The outcome of this step is shown in Table 2.

At this stage, the (number of defaults/the number of clients) for each decile represents the 7-year (y-year) cumulative default frequency, which we transform into an x-year default frequency using the following formula:[25]

$$PD_{x-year} = 1-(1-PD_{y-year})^{(x/y)} \qquad (2)$$

Therefore, to convert the 7-year cumulative default frequency into a 1-year counterpart we perform the following transformation:

$$PD_{1-year} = 1-(1-PD_{7-year})^{(1/7)} \qquad (3)$$

5) Taking the central value of each decile of the 1-year PD distribution (see the final two columns of Table 2), and interpolating these points with the corresponding ex-post default frequency we find a function (exponential) which can be used to transform the score in PD into Moodys rating terms.

[TABLE 2 ABOUT HERE]

Figure 4 reports the outcome of this mapping to Moodys ratings grades for our sample where the following annual cumulative default frequencies (DF) were used to delineate the Moodys categories: Aaa: DF=0.02%; Aa: DF=0.07%; A: DF=0.15%;Baa: 0.73%; Ba: 3.16%; B: 10.95% and CCC-D: DF > 10.95%. For example, from the figure we see that according to the RANK model

[25] It should be highlighted that the proposed formula assumes a linear relationship between the PD and time. While empirical evidence confirms such a relationship for investment-grade borrowers, this is generally not true for high-yield clients. Indeed, for the latter class of borrowers the relationship between time and PD is characterised by a concave shape.

0.3% of our sample companies are rated AAA, while 35.3% are rated BBB. Furthermore, we report in Table 3 the yearly breakdown of defaults across the different Moodys categories.

[FIGURE 4 ABOUT HERE]

[TABLE 3 ABOUT HERE]

4.3 LOGIT Model

The LOGIT model is given by the following general specification:

$$PD = \frac{1}{1+e^{-Z}} \tag{4}$$

where

$$Z = \alpha + \beta_1 X_1 + \ldots + \beta_n X_n \tag{5}$$

Our application of the LOGIT model, due to the very different nature of the approach, relies on a different dataset which is represented in Table 4. The first column indicates the year of default while the second column the number of defaulting companies for each year. Then, on the basis of the yearly PD applicable to the Italian Banking System for non-financial borrowers (‘PD_{ITB}’ – third column), the number of performing companies for each year is estimated by dividing the number of defaulting companies for each year by the default frequency of the system for that year (Number of Companies in Default / PD_{ITB} – fourth column). Then, on the basis of the half year in which the default occurs, we establish which year balance sheet should be used (fifth column). The sixth column of Table 4 indicates the number of balance sheets of defaulted companies to be considered for each year.

[TABLE 4 ABOUT HERE]

Consider the following example. In 1994 and in 1995 there are, respectively, 30 and 81 companies in default. Upon checking which half year the default occurs we find that the 30 companies in the 1994 have defaulted during the second half of that year and therefore, for all these companies we consider the 1993 balance sheet. In 1995 we find that for 33 of the 81 defaulting companies the default event happened during the first semester of the year (41% - see column 8), and only for these companies we refer to the 1993 balance sheets. Thus the total number of defaulting company balance sheets used for 1993 is 63 (30 + 33). The number of “balance sheets” of performing companies to be considered in 1993 (column 9), is then calculated in the following way: 847*100%+2,562*41%=1,891. The resulting total dataset is made up of 39,638 performing (bottom of column 9) and 936 defaulting companies, totalling 40,574 statistical observations.

In our application of the logit approach we utilize transformed data, whereby the explanatory variables are converted into dichotomous variables (0 or 1). More specifically, we use the information produced by the univariate analysis on each balance sheet indicator to divide each series into quintiles, and successively transform each quintile into 5 dichotomous variables. For example, the series of ROIs will be transformed into 5 dichotomous variables (ROI1, ROI2, ROI3, ROI4, and ROI5). Hence, for a given company only that ROI variable associated with the quintile in which the company is classified will assume a value of 1, all other ROIs will take a value of zero for that company.

The dependent variable of the LOGIT model is binary – it takes a value of zero for performing companies, and unity for defaulting companies. The independent variables of the LOGIT model initially comprise 70 dichotomous variables, coming from 14 balance sheet ratios that each have been converted into five quintile based dichotomous variables. At this point, a forward selection process is adopted, and starting from the most powerful indicators (regarding profitability, leverage, firm size and liquidity), other indicators are taken into account looking at whether they add statistical significance to the group. Ultimately we found seven balance sheet indicators being significant in explaining the probability of default of our 1994 data sample. The resulting equation is shown in Table 5.

[TABLE 5 ABOUT HERE]

To validate the LOGIT model, we look at the sign of the coefficients, their statistical significance and for the same variable we also look at the sign and the tendency – ie. an increasing or a decreasing tendency – of the various coefficients on the 5 sub-variables (dichotomous variables) in which each indicator has been transformed.

To better appreciate the latter two points, it could be helpful to recall the structure of the LOGIT regression together with some output obtained with our LOGIT model. In a “classic” LOGIT regression, the sign of estimated coefficients is important to see whether the contribution of each ratio goes in the direction of increasing or decreasing the probability of default, in line with expectations. In the case of LOGIT regression on transformed data (as previously described) this evaluation cannot be based solely on the sign but also on the “tendency” of the coefficient as the ratio increases (decreases). For example, consider the ROI variables in the LOGIT model. We can see that as ROI increases (ROI1, …, to ROI5), the estimated coefficients generally decrease –the highest ROI, indicates only a minor contribution to the total score, other things equal. Conversely, the lowest ROI category (ROI1), having a significantly positive coefficient implies a significant PD increase, consistent with expectations. Therefore, both the sign and the tendency of the coefficients are important because their conjoint analysis allows a clear understanding.

Figure 5 (similar to Figure 4 in the case of the RANK model) reports the outcome of mapping from LOGIT model outcomes to Moodys ratings grades for our sample. For example, from the figure we see that according to the LOGIT model about 7% of our sample companies are rated AAA, while 55.7% are rated BB. These assignments are considerably higher for these categories than obtained from the RANK model (refer back to Figure 4).

[FIGURE 5 ABOUT HERE]

At this stage, we have obtained two PD estimates based on an analysis of historical data (one each coming from the RANK and the LOGIT approaches). In terms of the dataset construction methodology, the LOGIT approach can be considered a 'myopic' probability of default because it uses as input only balance sheets up to one year distant to (potential) default. In contrast, the rank approach could be interpreted as a 'long-sighted' probability of default since it looks at a given year companies' balance sheets and follows the evolution of these companies for a long period of time (7 years).

4.3 Bottom-up Model Cross-validation

An informative cross-validation involves assessing the same dataset of borrowers (out-of sample) employing both approaches to see by how much the two models differ in classifying the same companies in different ratings classes. Accordingly, this has been done on a common sample of 23,067 companies of which 832 defaulted during the period 1999-2001 and the results are shown in Table 6. From the table we see that while the two models produced identical rankings for a relatively low 37.9% of cases, adjoining ratings were produced nearly 90% of the time.

[TABLE 6 ABOUT HERE]

The validation phase of the analysis in which we tested the soundness of various models proved to be very challenging as it became clear that it is often difficult, if not impossible, to choose the "best" specified model. Indeed, while we could identify very strong models that rated 85-90% of the companies correctly, it was still possible to find an alternative model able to correctly rate the 10-15% mis-rated by the first model. However, a more in-depth analysis of the second model revealed that it would give an incorrect rating for a different subset of the data (another 10-15%). To resolve this problem, we decided to use both approaches, as follows:

a) Take the PD obtained by the two models in the case of convergence of the rating given to the same company;
b) In those cases where the models give different results, but within three notches of each other, we take the result of that model which assigns a more severe PD to the client (conservative approach);

c) In those cases where the PD assigned by the two models to a given company are considerably different from one from each other (ie > three notches), we require additional information and therefore more carefully scrutinize the balance sheet of the company before assigning a rating.

5. PD Corrections – Macroeconomy and Client-Bank Relationship

Our one remaining task is to transform the historical PD into a prospective or forward-looking PD. We enhance the predictive feature of our model results by considering a correction based on the influence of macroeconomic factors on the probability of default. Specifically, this transformation of the historical PD (obtained using the bottom-up approach) into a prospective PD, takes into account consensus expectations on factors such as GDP, inflation, short- and long-term interest rates. An added benefit of considering the consensus forecasts on macroeconomic factors is it will likely help us to address the correlation effect amongst borrowers belonging to the same industry. The data available comprises 13 economic sectors and different types of borrowers, over the period 1984 to 2001.

We have identified two ways to address the influence of macroeconomic scenarios on the default probability estimated by the bottom-up approach: (1) a multi-factor model approach, and (2) the 'default'-clock type approach.

5.1 Multifactor Model Correction

In the first case, the top-down approach involves a multi-factor model in which the dependent variable, the probability of default for each economic sector, is linearly linked to shocks of macro-economic variables, such GDP, unemployment, real interest rates, inflation, long term interest rates and their lagged values. This approach can be simply represented by the following equation:

$$\Delta PD = \beta_o + \sum_{k}^{n} \beta_k X_k + \varepsilon \qquad (6)$$

where ΔPD represents the change in the probability of default for each sector and geographic area, and X_k represent the various macroeconomic factors. Once the equilibrium relationship amongst default rates and macroeconomic factors has been estimated and consensus data on these factors for the next year are available, it is possible to obtain an indication of whether the value of the prospective PD should be more or less severe than the historical PD. Consider the following example.

We estimate the following model that relates the change in PD to the change in GDP, to the change in the short-term interest rate and to the CPI:

$$\Delta PD = -0.0512\,ChangeGDP + 0.5072\,ChangeShort + 0.03CPI \tag{7}$$

All coefficients of this model are significant at the 1% level, with an R^2 (adjusted R^2) of 0.732 (0.688). Now suppose that we obtain the consensus forecasts on the three macro-economic factors as follows: ΔGDP = +2,5%; Δshort-term interest rate = +1%; and Inflation= 3%. Based on the previously identified estimated equations, we can quantify the estimated impact on the historical PD as:

$$\Delta PD = -0.0512 \times 2.5 + 0.5072 \times 1 + 0.03 \times 3 = +0.4692$$

That is, the historical PD obtained by the integrated multi-model should be increased by 0.004692% to obtain a prospective PD.

5.2 Default-Clock Correction

The second top-down approach that we experiment with to correct the historical PD is an extension of the Merrill Lynch Investment Clock – in our case, a so-called 'default clock'. Specifically, Merrill Lynch has developed an asset allocation technique which considers only four possible macroeconomic scenarios, and on the basis of the coming year's economic outlook, the approach suggests whether to invest in one or another class of assets. We extend this approach to correct the historical probability of default on the basis of the scenario assessment of the (macro) economy in the next year. The four scenarios are the following:

Default-Clock Economic Scenarios

		GDP	
		Decreases	Increases
Inflation	Decreases	'Soft landing'	'Recovery'
	Increases	'Hard landing'	'Overheated economy'

While for Merrill Lynch each scenario gives rise to different asset allocation advice, we have used the same approach to calculate the average default probability of each sector during each of the four phases of the economy. The first step is to calculate the average PD for each of the four phases. Then, we estimate whether the passage from one phase to another creates an aggravation or an improvement of the PD for each economic sector. This is achieved by determining a multiplier for each phase of the economic cycle and for each sector. The multiplier is simply determined by dividing the average PD of each sector for a given economic phase by the PD of the entire Italian system for the same economic phase.

In Figure 6 we depict our 'default-clock' for the Italian banking system. The average PD for each phase of the economic cycle is indicated within the circle, in the corresponding quadrant. Outside the circle we indicate by how much, passing from one phase to another, the PD should be altered – either positively or negatively. For example, if the economy is expected to move from 'recovery' into an 'overheated' phase then the probability of default needs to be reduced by 51 basis points – reflected by the average PD falling from 2.86% to 2.35%. Conversely, if the economy is expected to move from a 'hard landing' into a 'soft landing' phase then the probability of default needs to be increased by 50 basis points – reflected by the average PD rising from 2.27% to 2.79%. Therefore, because the period of our analysis, 1994-2001, was characterised by a 'soft-landing' phase of the economy, and the next year economists' consensus is indicating a 'recovery' phase, the historical PD should be corrected upwards by 7 basis points.

[FIGURE 6 ABOUT HERE]

5.3 Client-Bank Relationship Correction

An additional correction to the historical PD comes from the length of the relationship between the client and the Bank. It is interesting to note that analyses run on the distribution of defaults for classes of companies divided by company age does not show any significance in assessing the probability of default of borrowers (see Figure 7). However, the length of the relationship between corporate borrowers and the bank does reveal a significant effect. Specifically based on the sample analysed, an incremental correction of 17% should be made to the probability of default of those companies which have a lending age relationship with the bank of less than 3 years.

[FIGURE 7 ABOUT HERE]

6. Model Validation

The validation of the results obtained from the overall model, that is, the assessment of the quality of the model's output is achieved using the 'Accuracy Ratio' (Sobehart, Keenan and Stein, 2000). The accuracy ratio is related to Gini's concentration ratio which can be graphically represented by Lorenz's curve, also known as the 'power' curve. The power curve shows the number of defaulting companies excluded given a percentage of the sample excluded. For example, a power curve of a 'random' model – a model totally unable to discriminate between 'good' and 'bad' borrowers, will eliminate the same number of defaults by eliminating the first decile (of lowest PDs), the second decile and so on. Conversely, the power curve for the perfect model will see all the defaulters eliminated at the very end, with the very highest PDs. The accuracy ratio (AR) is the ratio of evaluated model's improvement over the naïve model versus the perfect model's improvement over the naïve model. So, the logic behind the AR statistic is related to the ability of the model to generate more extreme predictions, that is, predictions that deviate significantly from the mean, while remaining consistent. Our model is found to have an accuracy ratio of 49.8%.

7. Summary and Conclusion

In the current paper we extend and improve upon the bottom-up style of credit risk modelling and utilize a large sample of private company clients from the Bank of Rome (over the period 1995 to 2001) to test the model. The main aims of the present work are:

(1) To define an integrated multi-model approach for banks to assess the risk of each single borrower within their credit portfolio; this model is the result of combining two approaches, bottom-up and top-down approaches. The bottom-up approach is also compounded by a long-term (RANK model) and a short-term (LOGIT model) view of the probability of default of a given borrower.

(2) A model that adjusts for the 'creative' accounting techniques adopted by managers and takes into account the influence of macro-economic variables on the probability of default of each economic sector so as to infer the next year probability of default.

(3) To create an additional tool which helps banks in analysing the degree of valuation efficiency of non-listed companies.

The principal characteristics of the proposed methodologies of estimation are:

1) The adoption of a broad definition of 'default' – the credit rating deteriorates either in the category of non performing (i.e. default) or in that of doubtful loans;
2) The provision of two statistical approaches to assign a long-term and a short-term probability of default to each company-client of the bank, and the comparison of the results obtained from the two approaches;
3) The construction of an integrated multi-model formulated on the bank's operative client base of reference. To such an end a sample was made of businesses which were representative of the client base lent to by a bank;
4) The simultaneous use, in the assessment of risk, of variables relating to the companies' balance sheets, information related to the economic scenario and length of the relationship between client companies and the Bank;
5) The assessment of a single model for all the borrowers (with the exclusion of financial, insurance and public companies).

The validation sections show an elevated capacity of the multi-model for representing the bank portfolio's effective credit risk. The results show how, although the analysis of the economic trend data is important for monitoring the credit risk, a reasonable forecast and definition of the risk could be obtained from information on the borrowers' balance sheets. Furthermore, the analysis of economic trend can effectively add value to the assessment of the borrower imposing a correction to the PD resulting from a bottom up analysis.

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Table 1: Rank Model Dataset

This Table reports the yearly evolution of defaults in our sample of 10,228 private companies in the Italian economy over the period 1995 to 2001.

	Defaults	Frequency of Default
1995	129	1.3%
1996	156	1.5%
1995-1996	285	2.8%
1997	181	1.8%
1995-1997	466	4.6%
1998	169	1.7%
1995-1998	635	6.2%
1999	143	1.4%
1995-1999	778	7.6%
2000	114	1.1%
1995-2000	892	8.7%
2001	120	1.2%
1995-2001	1,012	9.9%
Number of Performing Cos	9,216	90.1%
Total Number of Cos	10,228	100%

Table 2: Back Test in Sample: Rank Model Score versus Default Frequency

This table reports the RANK model Score versus default frequency in our sample of 10,228 private companies in the Italian economy over the period 1995 to 2001. The data is sorted into deciles sorted on the RANK model score.

Decile Class	No of Companies	Max Score	Defaults	Cumulative Defaults	7-Year Cumulative Default Frequency	Median Score	Annualised Default Frequency
1	1,022	4.915	2	2	0.1957%	4.345	0.0280%
2	2,044	5.527	17	19	1.6634%	5.233	0.2393%
3	3,066	5.997	27	46	2.6419%	5.777	0.3818%
4	4,088	6.418	34	80	3.3268%	6.209	0.4822%
5	5,110	6.834	50	130	4.8924%	6.625	0.7140%
6	6,132	7.224	84	214	8.2192%	7.030	1.2178%
7	7,154	7.668	95	309	9.2955%	7.436	1.3841%
8	8,176	8.195	136	445	13.3072%	7.920	2.0193%
9	9,198	8.839	204	649	19.9609%	8.505	3.1307%
10	10,228	10.000	363	1,012	35.2427%	9.272	6.0187%
Total	10,228		1,012		9.8944%		

Table 3: Defaults over time and Moodys Ratings Categories

This table reports the yearly breakdown (numbers and percentages) of defaults of our private company sample across the different Moodys ratings categories.

Panel A: Raw Numbers

	AAA	AA	A	BBB	BB	B	CCC	Defaults
1995	-	-	-	3	17	75	34	129
1996	-	-	-	8	49	85	14	156
1995-1996	-	-	-	11	66	160	48	285
1997	-	-	-	22	66	80	13	181
1995-1997	-	-	-	33	132	240	61	466
1998	-	-	1	27	55	75	11	169
1995-1998	-	-	1	60	187	315	72	635
1999	-	-	1	15	64	52	11	143
1995-1999	-	-	2	75	251	367	83	778
2000	-	-	1	20	47	45	1	114
1995-2000	-	-	3	95	298	412	84	892
2001	-	1	2	24	55	33	5	120
1995-2001	-	1	5	119	353	445	89	1,012
Number of Performing Companies	30	393	980	3,494	2,999	1,255	65	9,216
Total Number of Companies	30	394	985	3,613	3,352	1,700	154	10,228

Panel B: Percentages

	AAA	AA	A	BBB	BB	B	CCC	Defaults
1995	-	-	-	0.1%	0.5%	4.4%	22.1%	1.3%
1996	-	-	-	0.2%	1.5%	5.0%	9.1%	1.5%
1995-1996	-	-	-	0.3%	2.0%	9.4%	31.2%	2.8%
1997	-	-	-	0.6%	2.0%	4.7%	8.4%	1.8%
1995-1997	-	-	-	0.9%	3.9%	14.1%	39.6%	4.6%
1998	-	-	0.1%	0.7%	1.6%	4.4%	7.1%	1.7%
1995-1998	-	-	0.1%	1.7%	5.6%	18.5%	46.8%	6.2%
1999	-	-	0.1%	0.4%	1.9%	3.1%	7.1%	1.4%
1995-1999	-	-	0.2%	2.1%	7.5%	21.6%	53.9%	7.6%
2000	-	-	0.1%	0.6%	1.4%	2.6%	0.6%	1.1%
1995-2000	-	-	0.3%	2.6%	8.9%	24.2%	54.5%	8.7%
2001	-	0.3%	0.2%	0.7%	1.6%	1.9%	3.2%	1.2%
1995-2001	-	0.3%	0.5%	3.3%	10.5%	26.2%	57.8%	9.9%
% of Performing Companies	100%	99.7%	99.5%	96.7%	89.5%	73.8%	42.2%	90.1%
Total % of Companies	100%	100%	100%	100%	100%	100%	100%	100%

Table 4: Logit Model Dataset Construction Phases and Composition

The first column indicates the year of default while the second column the number of defaulting companies for each year. Then, on the basis of the yearly PD applicable to the Italian Banking System for non-financial borrowers (‘PD_{ITB}’ – third column), the number of performing companies for each year is estimated by dividing the number of defaulting companies for each year by the default frequency of the system for that year (Number of Companies in Default / PD_{ITB} – fourth column). Then, on the basis of the half year in which the default occurs, we establish which year balance sheet should be used (fifth column). The sixth column indicates the number of balance sheets of defaulted companies to be considered for each year. Column seven reports the percentage of column two defaulting companies that use this balance sheet data with a one-year lag. Column seven reports the percentage of column two defaulting companies that use this balance sheet data with a two-year lag. Consider the following example. In 1994 and in 1995 there are, respectively, 30 and 81 companies in default. Upon checking which half year the default occurs we find that the 30 companies in the 1994 have defaulted during the second half of that year and therefore, for all these companies we consider the 1993 balance sheet. In 1995 we find that for 33 of the 81 defaulting companies the default event happened during the first semester of the year (41% - see column 8), and only for these companies we refer to the 1993 balance sheets. Thus the total number of defaulting company balance sheets used for 1993 is 63 (30 + 33). The number of “balance sheets” of performing companies to be considered in 1993 (column 9), is then calculated in the following way: 847*100%+2,562*41%=1,891. The resulting total dataset is made up of 39,638 performing (bottom of column 9) and 936 defaulting companies, totalling 40,574 statistical observations.

Company Default Data		Italian Banking System		Balance Sheet Data – Defaulting Companies		Percentage		Balance Sheet Data – Performing Companies
Year	Number of Cases	PD_{ITB}*	No. of Performing Companies**	Year	Number of Cases	Year t+1	Year t+2	Number of Cases
1994	30	0.03540	847	1993	63	100%	41%	1,891
1995	81	0.03162	2562	1994	126	59%	55%	3,750
1996	143	0.03494	4093	1995	158	45%	55%	5,093
1997	168	0.02877	5839	1996	178	45%	65%	7,276
1998	158	0.02206	7162	1997	142	35%	67%	6,876
1999	129	0.01985	6499	1998	113	33%	65%	6,189
2000	110	0.01743	6311	1999	93	35%	46%	5,156
2001	117	0.01850	6324	2000	63	54%	-	3,405
Total	936			Total	936	-	-	39,638

* Probability of Default for the Italian banking system

** Calculated as: (Number of Companies in Default / PD_{ITB})

Table 5: Logistic Regression Analysis of the Likelihood of Default

The LOGIT model is given by the following general specification:

$$PD = \frac{1}{1+e^{-Z}} \tag{4}$$

where

$$Z = \alpha + \beta_1 X_1 + ... + \beta_n X_n \tag{5}$$

In this application of the logit approach we utilize transformed data, whereby the explanatory variables are converted into dichotomous variables (0 or 1). More specifically, we use the information produced by the univariate analysis on each balance sheet indicator to divide each series into quintiles, and successively transform each quintile into 5 dichotomous variables. The dependent variable of the LOGIT model is binary – it takes a value of zero for performing companies, and unity for defaulting companies. The independent variables of the LOGIT model initially comprise 70 dichotomous variables, coming from 14 balance sheet ratios that each have been converted into five quintile based dichotomous variables. At this point, a forward selection process is adopted, and starting from the most powerful indicators (regarding profitability, leverage, firm size and liquidity), other indicators are taken into account looking at whether they add statistical significance to the group.

Variable	Coefficient	Standard Error	z-stat	P-value
CORP	-2.1170	1.0099	-2.0962	0.0361
POE	0.0061	0.0906	0.0673	0.9463
Lev1	-1.4045	0.1356	-10.3577	0.0000
Lev2	-1.0074	0.1138	-8.8524	0.0000
Lev3	-0.9612	0.1115	-8.6206	0.0000
Lev4	-0.6152	0.1016	-6.0551	0.0000
Lev5	-0.2028	0.1157	-1.7528	0.0796
COPOF1	0.6481	0.3397	1.9079	0.0564
COPOF2	0.5185	0.2955	1.7547	0.0793
COPOF3	0.2575	0.2968	0.8676	0.3856
COPOF4	0.1491	0.2968	0.5024	0.6154
COPOF5	0.0318	0.3227	0.0985	0.9215
AMANT	-1.3652	0.4565	-2.9906	0.0028
ROI1	0.6430	0.2427	2.6494	0.0081
ROI2	0.2253	0.1797	1.2538	0.2099
ROI3	0.2167	0.1645	1.3173	0.1877
ROI4	0.2070	0.1538	1.3459	0.1783
ROI5	-0.0307	0.4576	-0.0671	0.9465
OFR1	-2.0678	0.1920	-10.7698	0.0000
OFR2	-1.6369	0.1539	-10.6361	0.0000
OFR3	-1.3109	0.1302	-10.0684	0.0000
OFR4	-0.6779	0.1000	-6.7790	0.0000
OFR5	-0.5937	0.1044	-5.6868	0.0000
AC1	-1.3155	0.2681	-4.9068	0.0000
Ac2	-1.4337	0.2608	-5.4973	0.0000
AC3	-1.4394	0.2588	-5.5618	0.0000
AC4	-1.4645	0.2563	-5.7140	0.0000
AC5	-1.2027	0.2580	-4.6616	0.0000

Table 6: Out of Sample Comparison between RANK and LOGIT Model Classification of Moodys Style Ratings

This table reports the outcome of an out of sample comparison of Moodys style ratings produced by the RANK and LOGIT models, performed on a common sample of 23,067 companies of which 832 defaulted during the period 1999-2001. The models produced identical (adjoining) ratings in 37.9% (89.23%) of cases.

Panel A: Number of Companies

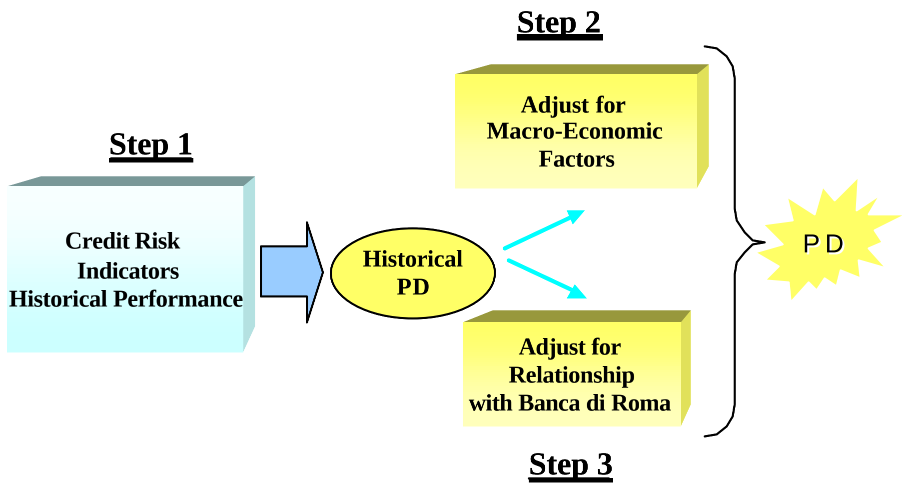
		LOGIT Model							
		AAA	AA	A	BBB	BB	B	CCC	Total
RANK Model	AAA	**41**	2	1					44
	AA	155	**249**	157	22				583
	A	99	344	**574**	348	38	1		1404
	BBB	78	322	988	**3051**	2168	413	49	7069
	BB	6	28	83	1168	**3191**	2687	1288	8451
	B			1	46	476	**1352**	3335	5210
	CCC			1	5	3	13	**284**	306
Total		379	945	1805	4640	5876	4466	4956	23067

Panel B: Percentage of Companies

		LOGIT Model							
		AAA	AA	A	BBB	BB	B	CCC	Total
RANK Model	AAA	**0.18%**	0.01%						0.19%
	AA	0.67%	**1.08%**	0.68%	0.10%				2.53%
	A	0.43%	1.49%	**2.49%**	1.51%	0.16%			6.09%
	BBB	0.34%	1.40%	4.28%	**13.23%**	9.40%	1.79%	0.21%	30.65%
	BB	0.03%	0.12%	0.36%	5.06%	**13.83%**	11.65%	5.58%	36.64%
	B				0.20%	2.06%	**5.86%**	14.46%	22.59%
	CCC				0.02%	0.01%	0.06%	**1.23%**	1.33%
Total		1.64%	4.10%	7.83%	20.12%	25.47%	19.36%	21.49%	100.00%

Figure 1:

Overall Structure of the Model



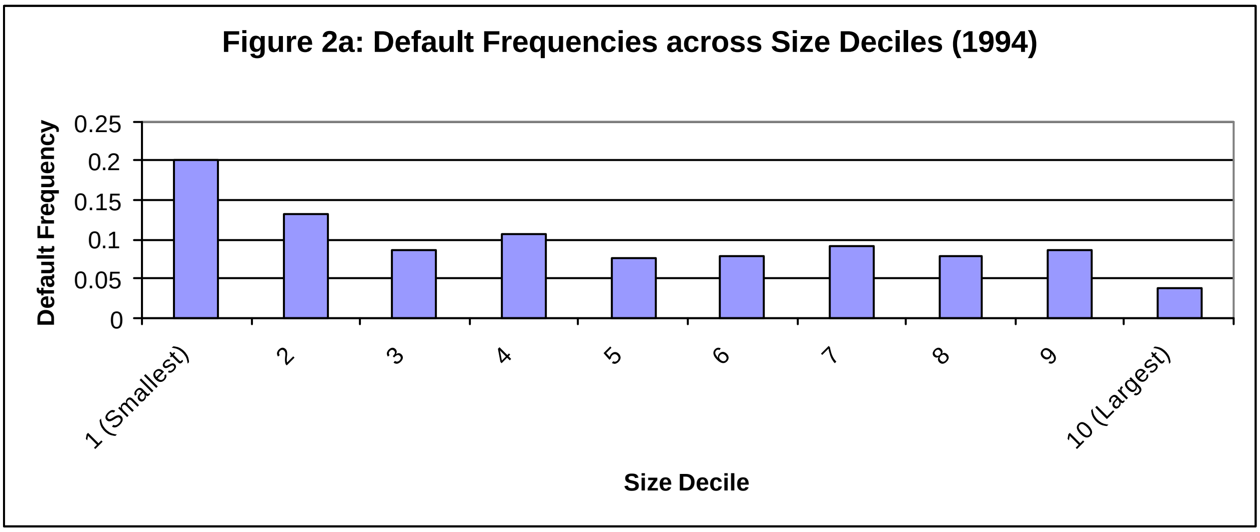


Figure 2a: Default Frequencies across Size Deciles (1994)
Default Frequency
0.25
0.2
0.15
0.1
0.05
0
1 (Smallest)
2
3
4
5
6
7
8
9
10 (Largest)
Size Decile

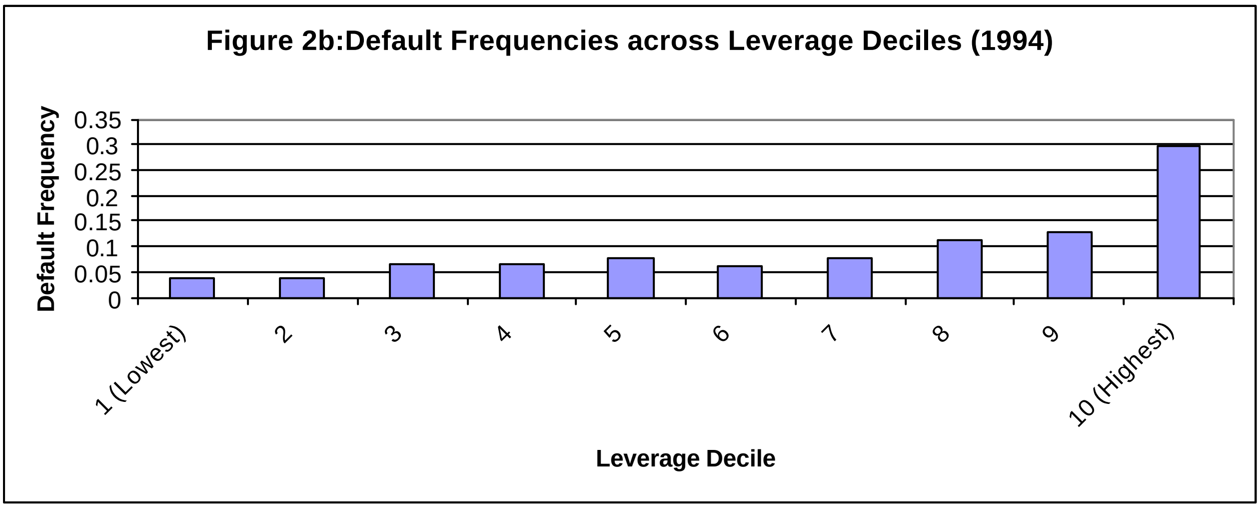


Figure 2b:Default Frequencies across Leverage Deciles (1994)
Default Frequency
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
1 (Lowest)
2
3
4
5
6
7
8
9
10 (Highest)
Leverage Decile

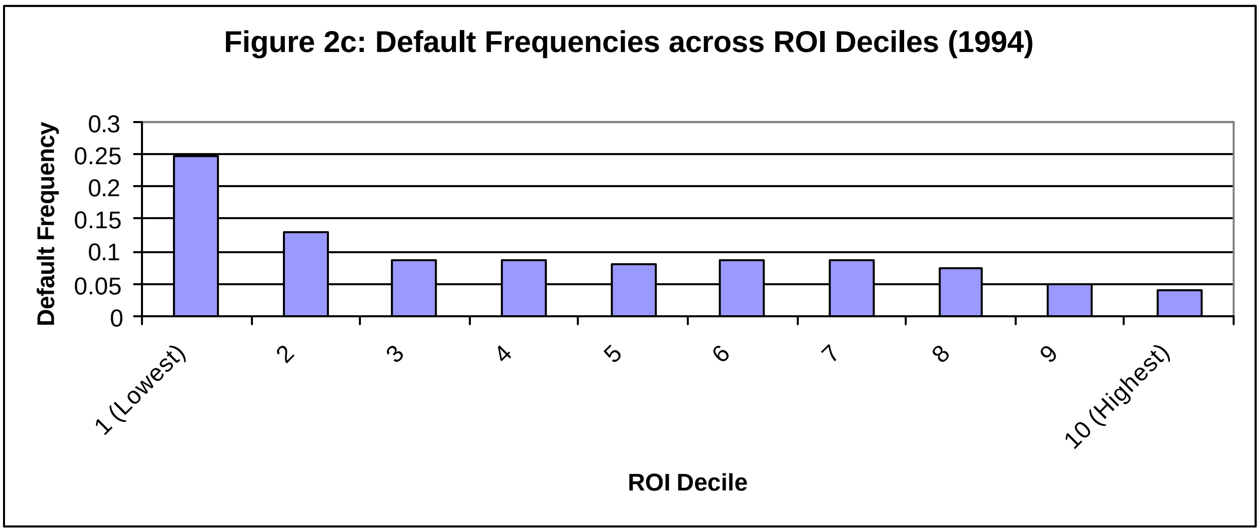


Figure 2c: Default Frequencies across ROI Deciles (1994)
Default Frequency
0.3
0.25
0.2
0.15
0.1
0.05
0
1 (Lowest)
2
3
4
5
6
7
8
9
10 (Highest)
ROI Decile

Figure 3: Indicators and Structure of the Integrated Multi-model Rating System

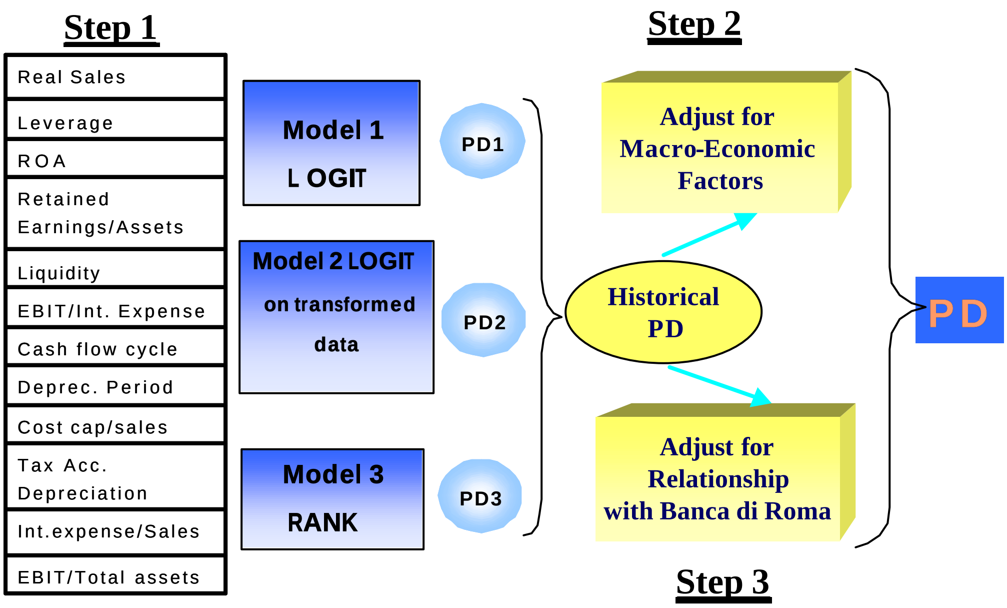


Figure 4: RANK Model Portfolio Composition in Terms of Moodys Ratings

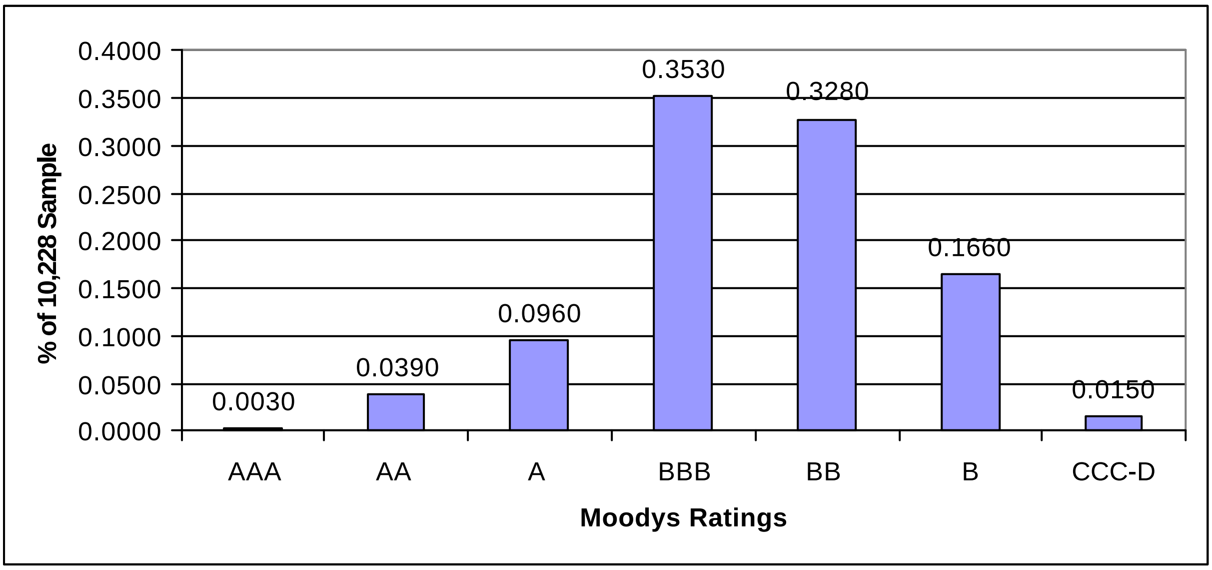


Figure 5: LOGIT Model Portfolio Composition in Terms of Moodys Ratings

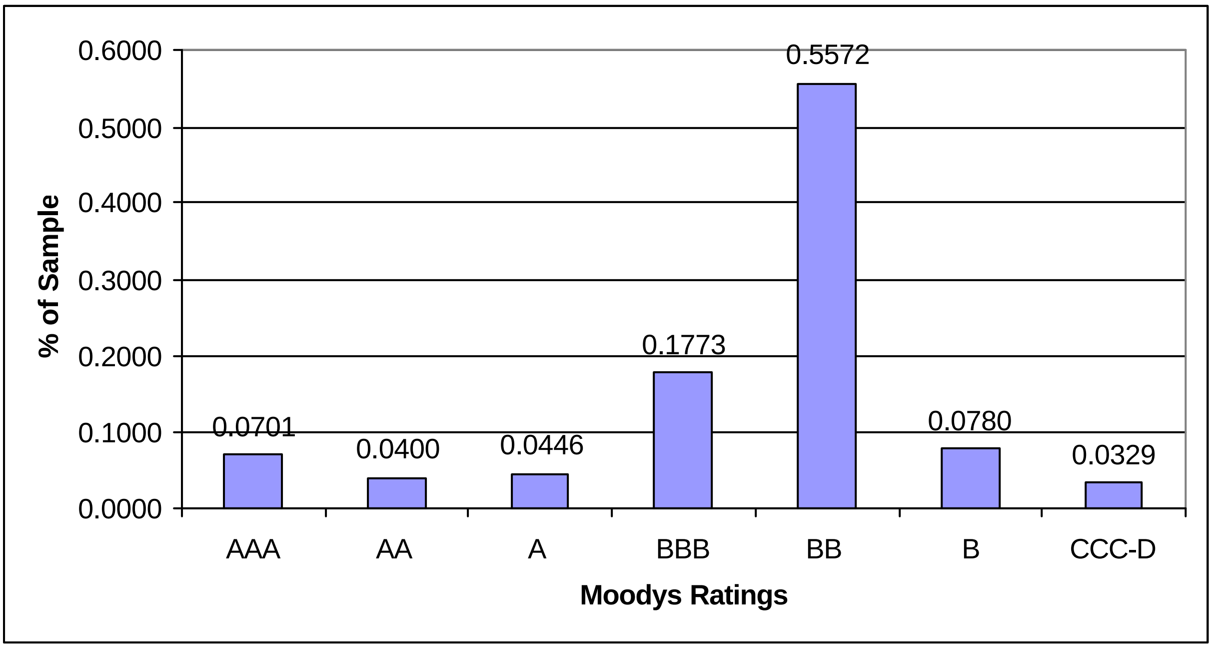


Figure 6: 'Default Clock' for the Italian Banking System

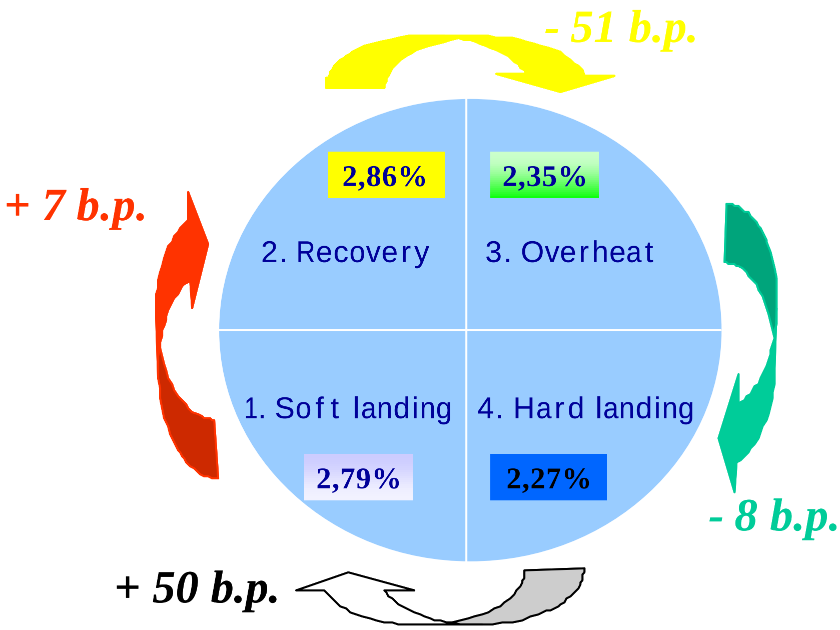


Figure 7: Number of Defaults per Deciles of Company Age