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Moody's RiskCalc™ For Private Companies: Italy

Rating Methodology

Overview

In recognition of the growing need for benchmarks in the rating of middle market companies, Moody's is creating models for estimating firm probabilities of default using financial statement data. This model is the latest in a suite of European models that are being co-developed with Oliver Wyman & Company, the leading global strategy consulting firm dedicated to the financial services industry. At the time of writing, this Moody's RiskCalc™ model for private firms in Italy joins RiskCalc™ private firm models for the US, Canada, Australia, Germany, Spain, France, the UK, Belgium, the Netherlands, Mexico, Japan and Portugal, allowing one to consistently attach probabilities of default to private firms throughout the world[1]. As a powerful, objective model, it serves the interests of institutions, borrowers and investors alike.

This report documents the following:

- Description of the database of financial statements used in developing Moody's RiskCalc™ for Italian private companies.
- Description of the methodology used to develop the model.
- Comparison of the relationship of various financial ratios to default.
- Empirical tests of the model.

The following is a self-contained description of the development and validation of the first version of the Moody's RiskCalc™ for Italian private companies. However, some details are omitted as a more detailed handling of some of the methodology is contained in "RiskCalc™ for Private Companies: Moody's Default Model".

1. For the most up to date list of available models, the reader is referred to the Moody's KMV website www.moodyskmv.com

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Introduction

Experience has shown that a key determinant of lending performance is the ability to assess correctly the credit risk within a portfolio. Default models, including objective quantitative models, are increasingly being used to assist in this effort. While we refer the interested reader elsewhere for the uses of default models, a selected list of applications includes the following:

- **Capital allocation:** In their efforts to ensure the soundness of the financial system and to encourage appropriate behaviour, regulators are increasingly looking for objective, hard-to-manipulate measures of risk to use in capital allocation.
- **Credit process optimisation:** While a single number may prove inferior to the judgement of a credit expert, the default model can help to pinpoint those cases where human judgement adds the most value.
- **Pricing:** Without an accurate measure of the risks involved in lending to middle market companies, shareholder value might be destroyed through sub-optimal pricing.
- **Securitisation:** Banks are increasingly seeking to offer their clients a full range of services, without holding the capital this would require. At the same time, investors are seeking new classes of risk, prompting a need for a transparent, objective rating standard.

Not only do all of these needs require a powerful, efficient tool that allows unambiguous comparison of different loans and companies, but the accurate pricing and trading of credit risk demands that any such tool is calibrated to a probability of default. RiskCalc is designed to provide an independent benchmark for most credit decision needs. We believe that in order for any tool to qualify as a benchmark it must satisfy the following conditions:

1 *It must be understandable.*

Customers consistently indicate that it is more important for them to understand why a model works than for it to provide marginal improvements in accuracy. The ratios driving a particular assessment should be clear and intuitive.

2 *It must be powerful.*

A model which is unable to differentiate between good and bad companies is clearly of little use in credit decisions. A consequence of a powerful tool is the willingness of experienced personnel to use it in pricing and decision making.

3 *It must be calibrated to probabilities of default (PDs).*

While a model that has not been calibrated can be used to decline or accept credits, it is of little use in ensuring that any risk assumed is accurately priced and capitalised. Furthermore, it will be of little use for trading debt.

4 *It must be empirically validated.*

Without documented performance on large datasets, prudence dictates that a third-party model must be viewed sceptically. Such testing also gives the user confidence that the model is stable and has not been "overfitted"[2].

If a model does not satisfy these criteria then, while it may be a useful tool, it cannot be considered a benchmark for the market. For example, market participants could not use a more powerful tool in secondary market transactions if it had not been calibrated. While we are confident that the model we have developed for Italy is very powerful, we concede that more powerful models could exist. Nevertheless, the products that form the RiskCalc suite are capable of being true benchmarks: they are easy to use, intuitive, powerful, calibrated, and validated.

RiskCalc™ for Italian private companies[3] has been developed in cooperation with Oliver, Wyman & Company, the leading global strategy consulting firm dedicated to the financial services industry and with extensive experience in developing similar models for many of the largest banks in Europe.

2. *Of course, the level of validation that can be performed depends on the amount of data that is available.*
3. *By "private firm" we refer to those firms who do not have publicly quoted and traded equity.*

Data Description

The intention of the RiskCalc™ suite of models is to provide credit risk benchmarks for those firms not covered by reputable rating agencies. The goal of RiskCalc™ for Italian private companies is to provide a probability of default (PD) for private Italian companies with turnover of more than €500,000[4]. However, use of a single model to cover all company types and industries is often inappropriate due to the very different nature of some firms. Thus we eliminated the following types of companies from our analysis:

- **Listed companies** – We believe that market valuation is a key element in assessing the likelihood of default of a publicly listed company.
- **Small companies** – The future success of the smallest firms is often as dependent on the finances of the key individuals as that of the company. For this reason, we excluded companies that never had turnover of more than €500,000.
- **Start-up companies** – Our experience has shown that the financial statements for a company during its first two years are extremely volatile and are a poor reflection of the creditworthiness of the company. The special nature of start-ups is reflected by the fact that many banks have separate credit departments for dealing with these companies.
- **Financial institutions** – The nature of financial institutions means that their balance sheets tend to exhibit significantly different characteristics from those of other private firms, for example relatively high gearing/leverage. Furthermore, the fact that financial institutions are generally regulated, and often required to hold capital, suggests that they are best considered separately.
- **Real estate development companies** – The success or failure of a real estate development and investment company often hinges on a particular development, so that the annual accounts rarely capture the true likelihood of default[5]. For this reason we excluded pure real-estate development companies.
- **Public sector institutions** – Rating public sector companies is complicated by the fact that the states or municipalities that use or own them have historically been unwilling to allow them to fail.

It is a widely accepted fact in the financial analysis and accounting communities that small companies' financial statements are on average less accurate and of lower quality than those of bigger companies. Therefore, we further cleaned the database to ensure that we did not select a model based on spurious power driven by poor data. For example, we excluded financial statements from our database based on plausibility checks of particular positions in financial statements (e.g., assets less than zero) or where the financial statement covered a period of less than twelve months.

In pre-development discussions with Italian banks, it became clear that the quality of the data that was available from commercially available financial statement databases was a concern. In order to address this concern, our Italian sponsor banks reviewed the statements that we had available, and highlighted those which contained erroneous information. In order to ensure that the RiskCalc Italy model was developed on data of the highest quality, those statements which contained poor quality data, together with those statements which were not reviewed, were excluded from development.

Table 1 provides a summary of the data sets used in development, validation and calibration of RiskCalc™ for Italian private companies and compares it with those used in developing other RiskCalc™ models. Once again we have had access to a large database of financial statement and credit event information, allowing us to develop a powerful, robust model.

Table 1

Information On Private Firm Sample Data

Country	Time Span	Unique Firms	Unique Firm Defaults	Financial Statements
Italy	1995-1999	52,327	958	124,937
UK	1989-2000	64,531	4,723	283,511
France	1990-2000	253,268	25,229	1,323,754
Spain	1992-1999	140,790	2,265	569,181
United States	1989-1999	33,964	1,393	139,060

4. In general the suite of RiskCalc™ Private Firm models are intended for use on firms above a sales/turnover threshold of approximately €500,000 or asset base of approximately €250,000.

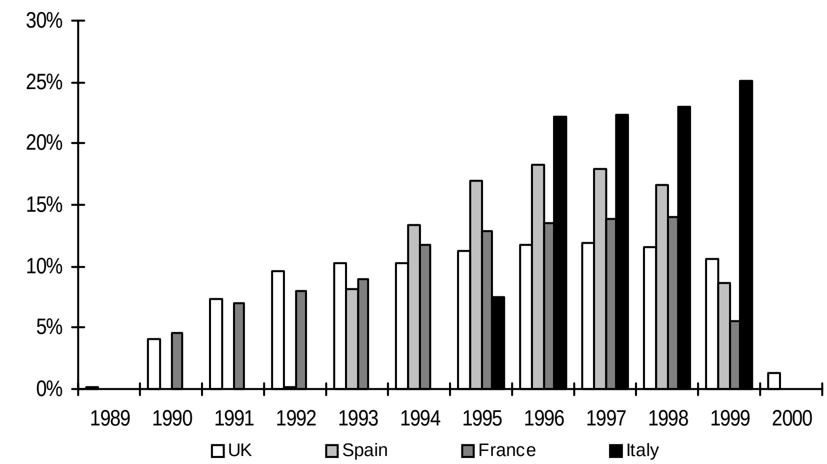
5. This is also the case for many types of "project finance" firms, (e.g., ship building firms), and we would recommend use of separate models for these. At the time of writing, this characteristic is explicitly recognised within the proposals for the new Basel capital accord.

The real advantage of databases of this size is the number of unique defaults available to us, allowing us to use substantial samples of defaults in developing and testing the model. The benefit of having a large number of defaults within development is obvious since by estimating the model's parameters on a large sample, the model is able to capture a more accurate picture of the relationship between financial ratios and the state of default.

The distributions of a sample of the European private firm data sets across years can be seen in **Figure 1**. This illustrates the difference in coverage between the RiskCalc™ Italy data set and the data sets available in other countries. The shorter time period covered by the Italian data set reflects the difficulty of checking the data quality of Italian statements more than a few years old.

Figure 1

Distributions Of Financial Statements Across Years



Statements with a turnover of between €2.5m and €10m made up over half our data set, while larger firms comprised about 20%. The size distribution of the statements used in developing and calibrating RiskCalc™ Italy is illustrated in **Figure 2**.

Figure 2

Distribution Of Financial Statements By Sales Class

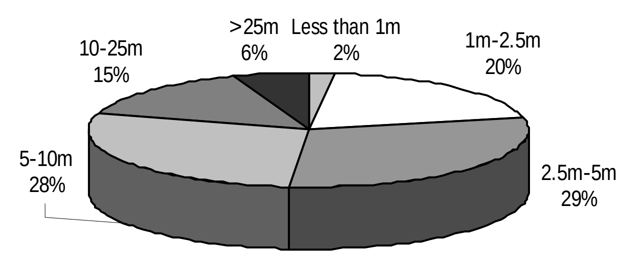
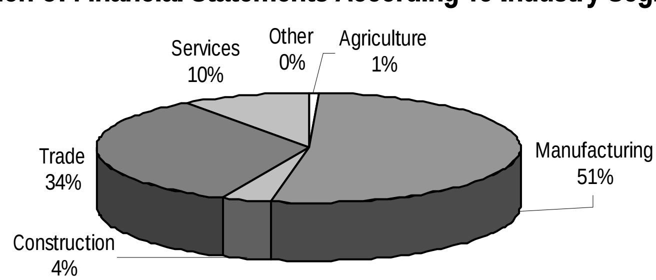


Figure 3 shows that about half the "approved" database consisted of manufacturing firms, with another third of the statements from trade companies[6].

Figure 3

Distribution Of Financial Statements According To Industry Segments



6. *Readers are referred to other RiskCalc™ documents for the industry distributions of the databases used in developing other models.*

Definition Of Default

Our intention in developing RiskCalc™ for Italian private companies, as with the other RiskCalc™ rating tools, is to provide assistance to banks and other institutions or investors in determining the risk of incurring losses as a result of company defaults, missed payments, or other credit events. The proposals for the new Basel Capital Accord (BIS II) have engendered lively debate about what constitutes an appropriate definition of default, with many banking organisations suggesting that some of the definitions would be inappropriate in certain markets. Thus, for example, whilst a "90 days past due" definition of default might be considered reasonable in Spain and several other European countries, the ABI[7] (an Italian banker's association) in its response to the proposals for the new Basel Capital Accord, indicates that a 90 days past due definition "*…represents a major difference from standard Italian accounting practices and Italian supervisory regulations…*" and "*suggest a 180-day period for medium and long-term loans*".

One of the aims of the RiskCalc™ suite of products is to provide a market benchmark not only for comparing the probability of firm default within a country, but also to allow meaningful comparison across countries[8]. This might appear to be in conflict with the BIS II related discussions. However, our experience and recent discussions with banks indicate that the common underlying concern for bankers is the risk of incurring credit losses. Thus where bankers have suggested that "90 days past due" is inappropriate, it is generally because they feel that firms, or certain types of firms, passing this point may not be experiencing difficulties[9], and that no credit loss is expected.

The discussion about the definitions of default included within the BIS II proposals appears to have centred around when a firm would be considered to have defaulted, and hence the impact on aggregate default rate numbers and PDs. There has been less discussion on how different default definitions might impact the variables used within internal rating tools. Our understanding is that this is because, as our own experience shows, the factors that can predict default are generally the same, whether the definition of default is 90 days past due, bankruptcy, or something in between.

The development of RiskCalc™ for Italian private companies differs from the development of some of the other RiskCalc™ models in that, in developing the first version of the model for Italian private companies, we have used publicly available data and have relied on corporate insolvency events[10] to identify the key indicators of credit losses[11]. The definition of default targeted when calibrating the RiskCalc™ for Italian private companies model is described in the following section[12].

Aggregate Probability Of Default Assumptions

The intention in developing the RiskCalc™ suite of products is to assist banks and investors in determining the probability of incurring credit losses. Thus in calibrating RiskCalc™ models to probabilities of default, we look beyond the events used in development to a broader category of credit events. There are two guiding principles in determining the appropriate definition of default to which to calibrate:

- **Consistency across RiskCalc™ models** – whilst a tool may be powerful and able to identify firms which subsequently default in a country, if it does not provide a measure which can be easily compared across countries, it will fail to meet the increasingly international needs of bankers, investors and regulators alike. At the same time the output of the model needs to be recognised as meaningful by the many credit professionals within a country, otherwise it will fail to gain credibility or acceptance, and will be destined to become irrelevant.
- **Consistency with regulatory requirements and capital rules** – a model which fails to be consistent with regulatory requirements and capital rules will also fail to gain wide acceptance since the role it plays in pricing and capital allocation decisions will be limited.

The concept to which we calibrate the RiskCalc™ models is that of a real expectation of a credit loss (on interest or principal), independent of the collateral position of an obligor.

7. Associazione Bancaria Italiana.

8. We believe that those private firm score-cards which do not fit into a global network of models, and hence do not allow users to make such comparisons, are considerably less useful, particularly for secondary market activities and for institutions with an international perspective.

9. The ABI refers, within its Basel response, to "the frequent cases of restoration of performing status not long after the expiration of the 90-day limit"

10. Our experience is that many factors which are useful in identifying firms at risk of entering insolvency are also powerful at identifying firms which are likely to default on payments to banks. This was confirmed by the robust results from the testing of our model at sponsor banks, which used their own definition of default.

11. As part of the development of the RiskCalc Italy model, the Italian Sponsor banks provided us with feedback on the performance of some interim models on their data, as well as discussing appropriate ratios with us. This provided us with insights which were incorporated when defining the final RiskCalc Italy model.

12. More details on the calibration of the model are contained within the Model Description section later in the document. Briefly, the calibration step maps the output of an algorithm to a probability of default.

The estimate of an aggregate probability of default is important because it serves as an anchor point for the model. Changing it upwards will move all predicted probabilities of default upwards and *vice versa*. In deriving this estimate, it is important to consider the structure of the sample used in developing and calibrating a rating tool as well as its intended use. Thus a model that was developed for use only on the very largest Italian firms, would have a very different anchor point PD from one developed for use only on the very smallest. Users should therefore bear in mind that the figure we use as an anchor point has been selected because we believe that it is an appropriate figure for the database we have used in development and calibration of the model.

In addition to considerations about size, legal form, industry and regional composition, one also needs to consider the period covered in calibrating a rating tool. If the data set used in developing and calibrating a rating tool covered a whole cycle, then the anchor point to use for calibration of a model would be the long-run average default rate[13] (which would be equal to the observed default rate). However, where this is not the case (in most situations), one should use an anchor point which lies somewhere between the period observed default rate and the long-run average, depending on the extent to which the rating tool captures changes in credit quality through the cycle. A tool which captures more cyclicality should be calibrated to a figure which is closer to the observed figure, whilst a tool which captures less cyclicality should be calibrated to a figure closer to the long run average default rate.

We have used a number of data sources to triangulate an estimate of the anchor point PD to which to calibrate the RiskCalc Italy model:

- Sponsor bank experience
- Provisioning data
- Insolvency statistics

Sponsor Bank Experience

As part of its commitment to developing the RiskCalc™ suite of products, Moody's KMV has formed a RiskCalc™ Sponsor Group consisting of several major European financial institutions from around Europe. One of the benefits of these relationships is that it has allowed us access to portfolio level default experience for two of the largest Italian commercial banks[14]. This access has allowed us to derive a robust estimate of the anchor point PD for the model[15].

Provisioning Data

In addition to this rich source of bank default experience, we analysed Italian banks' loan loss provisions, which, over time, will tend to equal actual losses and hence reflect the underlying default rate. Loss rates and default rates are tied together by the loss given default rate (LGD) using the following formula:

$$\textit{Volume of Losses} = \textit{Volume of Loans} \times \textit{Probability of default} \times \textit{LGD}$$

$$\Rightarrow \textit{Probability of Default} = \textit{Volume of Losses} \,/\, (\textit{Volume of Loans} \times \textit{LGD})$$

Insolvency Statistics

A further "point" used in triangulating to our central tendency was analysis of national insolvency statistics. Care was taken in moving from these national figures to a central tendency number since these aggregate figures were in part driven by size, industry and legal forms not covered by RiskCalc™ for Italian private companies.

Based on these analyses, considerations concerning the cyclicality of the rating tool and the underlying data set used in calibrating the RiskCalc Italy model, as well as discussions with Italian banks, we have used an anchor point of 2.1% for the 1 year PD.

In deriving the anchor point for the cumulative 5 year PD, we have again faced challenges given the relative lack of publicly available data. In developing the North American private model, Moody's KMV spent considerable time in examining the relationship between the 1 and cumulative 5 year PDs[16] and the result of this work provides the initial basis for deriving a 5 year cumulative anchor point. The benefit of this work is that it covers a substantial period of time, and can be used to supplement the information provided by our database. The results of these analyses suggest that 5 year cumulative default rate is, on average[17], approximately 4 times the level of the 1-year default rate. Thus in calibrating RiskCalc™ Italy for the 5-year horizon, we have used an anchor point of 8.4%.

13. This assumes that there has not been a structural shift in default rates, (e.g., in the US, post the oil shocks).
14. The initial press release (dated October 18th 2001) announcing the formation of the RiskCalc™ Sponsor Group, and a subsequent release announcing the addition of further banks can be found on Moody's KMV website.
15. As discussed above, the figure selected in calibrating a model should reflect the scope of the database used during development of a rating tool and intended use of a rating tool. Thus the anchor point used in calibrating the RiskCalc Italy model reflects the composition of our data set, and is not an indication of the credit quality of the sponsor banks' portfolios.
16. For more details on this work, we refer the reader to the description in "RiskCalc™ For Private Companies: Moody's Default Model".
17. Bond default studies (e.g., Moody's Special Comment, January 2000, "Historical Default Rates of Corporate Bond Issuers, 1920-1999"), and experience working with bank loan portfolios, show that the relationship between 1 and 5 year cumulative default rates varies by credit quality. Thus, whilst the "average" is a factor of 4, the average 5 year cumulative default rate for Aa rated bonds is more than 10 times higher than the average 1 year default rate. This variation is caused by credit migration, whereby the credit quality of highly-rated firms tends to deteriorate, whilst poorly-rated firms, if they survive, improve in credit quality.

Model Description

RiskCalc™ for Italian private companies is a non-structural model in that it does not use an explicit specification of default based on theory, but it is highly informed by the collective default modelling experience of Moody's and Oliver, Wyman & Company. As in any quantitative modelling exercise, we face a trade-off between in-sample fit and out-of-sample robustness. Our modelling approach is towards the simplest functional form and the smallest number of inputs[18]. Our modelling approach can be briefly summarised in the following three steps:

- **Single Factor Analysis**: The aim of single factor analysis is to study the individual relationship to default of a set of potentially relevant factors that could be regarded, *a priori*, as independent variables in the final model. In this step we also mini-model the factors.
- **Model Specification and Estimation**: Once the individual factors have been analysed, the next step is to specify a model, using a subset of the most powerful factors. These factors are combined in a logistic model and their weights are optimised.
- **Calibration:** Finally, once the model has been specified and its weights estimated, the output of the model is mapped to a probability of default.

Single Factor Analysis

A specific characteristic of rating models based on financial statement information is the large number of variables that can be used to predict default. It is very easy to define several hundred financial ratios, combining all the useful information contained in the financial statements of a company to assess its credit worthiness. The way this information is used to build the model is crucial in determining the capability and robustness of the final model in predicting default. In particular, some of the financial ratios that can be derived will be useful to predict default, but others are likely to be spuriously related to the default variable. Furthermore, some of the ratios can take extremely high or low values for some companies, without adding any information for default prediction purposes. These two facts highlight the importance of the variable selection and transformation processes that are performed during the single factor analysis phase.

Given the large number of possible ratios, it is important to reduce the list of ratios that enter the final model selection process. This screening of ratios is based on the following criteria:

- *They must be intuitive*. If the final model is to be intuitive and make business sense, it must include factors that are intuitive and make business sense.
- *They must be individually powerful*. We want to keep in our set of potential factors, those that have a high discriminatory power between defaulted and non-defaulted companies[19].
- *There must be enough observations*. To be statistically comfortable with the results of the single factor analysis for a particular factor, there must be a large number of observations. Furthermore, a large number of missing values would generally indicate that the information is difficult to obtain, and hence it would not be prudent to include it in the final model.

It is important when considering which ratios to include in a model to have a prior expectation of how they will be related to default, otherwise one runs the risk of selecting a ratio based on statistical quirks. Thus, when a factor does not fit with our prior expectation, we exclude it from further analysis. Consider Equity / Assets, where we would expect higher values to be associated with lower probabilities of default. If the data indicated that higher values were associated with higher levels of default, then we would not include Equity / Assets in subsequent analyses.

We test the predictive power of each ratio using the accuracy ratio[20] which measures the ability of a metric to differentiate between firms that later went on to default from those that did not. Where a ratio has little predictive power, which corresponds to a low accuracy ratio, we exclude it from further analysis.

Having excluded counter-intuitive or uninformative ratios in the previous steps, we "mini-model" the remaining factors individually to capture their relationship to default. As shown in **Figure 4**[21]**,** this relationship is generally monotonic, meaning that the slope is either always positive, so that a higher ratio value indicates a higher probability of default (e.g. (Total Debts – Liquid Funds) / Assets), or always negative, so that a lower ratio value indicates a higher probability of default (e.g., (Net P&L + Depreciation) / Total Debts)[22]. It is also apparent from **Figure 4** that this relationship is generally not a straight-line relationship (i.e., it is "non-linear").

18. As well as increasing the cost of using a tool, a large number of inputs can have a negative impact on the usability of a model, which can in turn reduce its usefulness (a rating model which is so complicated that people do not use it on a day-to-day basis is not a very useful rating model).

19. This can be taken too far, since, in a multi-variate context, it is possible for some factors which are individually relatively weak, but which have a low level of correlation to other measures, to add new and useful information. Consider a model with two gearing ratios: whilst sales growth might be less powerful on its own than a third gearing ratio, it might be included because it is less correlated with the other gearing ratios, and hence adds more new information.

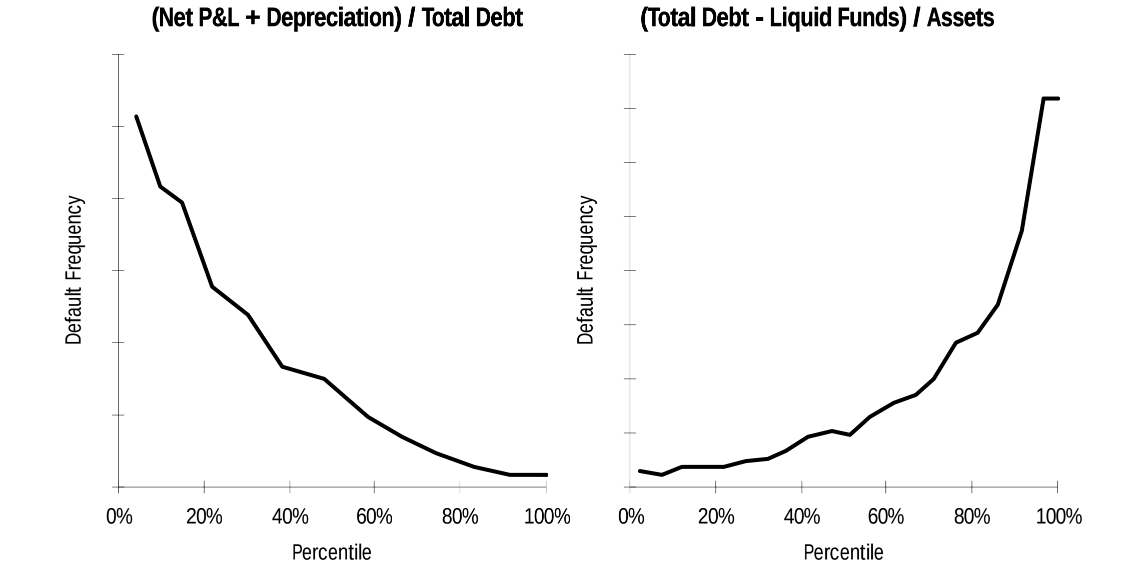
20. For more details on the Accuracy Ratio, see the section on Empirical Tests later in the document. Readers may be familiar with the accuracy ratio concept, but under a different name such as the power statistic or the Gini coefficient.

*21. The x-axis shows the percentile in which a particular ratio value lies and the y-axis shows the default frequency that is observed for firms with ratios in that percentile. For example, it can be seen from the profitability measure, (Net P&L + Depreciation) / Assets, that lower profitability values are associated with higher default rates. These two graphs are similar to the graphs shown on the right hand side of **Figures 5-12**.*

22. One of the most widely documented class of non-monotonic ratios, are growth ratios which often exhibit a U shaped relation with default.

Figure 4

The Relation Between A Financial Statement Ratio And Default Is Generally Monotonic And "Non-Linear"



Given this monotonicity we model the relationship to default so that we capture it in a smooth manner and "cap" extreme values[23]. This "capping" not only eliminates the impact of outliers in the estimation of the parameters of the final model, but ensures that the final PD for a firm is not distorted by the impact of a calculation quirk. It also reflects the fact that beyond a certain level, most ratios provide little additional information about default.

Model Specification And Estimation

In the second step, the selected transformed factors undergo a process of multivariate analysis to determine the predictive power of different combinations of these ratios. Starting with a list of 20 ratios there would be over 1 million possible models which could be created, so it is important to use statistical selection procedures such as forward, backward, and stepwise regression to reduce further the set of factors, and hence possible models.

Including highly correlated ratios when estimating the optimal weights for a model without careful attention to address this issue can result in unstable estimates of these weights, and poor performance of a model when applied outside the development sample. Furthermore, the weights assigned to these factors can often be counter-intuitive. For example it might be possible to have a model in which higher profitability led to higher default rates. Thus, when incorporating similar factors, we have been careful to examine the stability of weight estimates in different factor classes and sub-samples, ensuring that the weights for the factor category (e.g., profitability) are stable, before splitting the category weight between the ratios in the category[24].

There is no hard and fast rule in determining how many ratios a particular rating model should contain: too few and the model will not capture all the relevant information; too many and the model will be powerful in-sample, but unstable when applied elsewhere and will probably have onerous data input requirements[25].

In addition to playing an important role in checking the quality of the data used for developing RiskCalc Italy, the Italian sponsor banks also tested a number of interim models on their data, and then met with us to discuss the results. This discussion gave us insights as to how the different models and ratios were performing on bank customers and defaults. In specifying the final model, we combined information from these discussions, together with analysis of the performance of different models on our data and different sub-sets of our data, with our experience and a number of practical considerations, including:

- data requirements for the user should be as low as possible,
- the number of factors within the final model should be as low as possible,
- the factors and their weights should be intuitive, and
- the model should have high explanatory power.

23. As part of this process we also "normalise" the data by subtracting the mean factor value and dividing by the standard deviation, simplifying interpretation of results during model estimation.

24. Thus, for example we estimated weights for a model including only Net P&L + Depreciation over Total Debts, and for a model with only Ordinary P&L + Depreciation over Financial Expenses, as well as estimating these models across different sub samples and models with other debt coverage measures. This produced reliable estimates for the importance of debt coverage ratios (as measured by the "weight" assigned to them). This weight was then split between the two ratios based on their individual power and the behaviour of the model in different sub-samples.

25. Furthermore, from a statistical point of view, a large number of ratios increases the error/variance in the estimates of the weights for each factor.

Calibration

The final part of the modelling consists of mapping the output of the model to probabilities of default. This exercise can conceptually be divided into two parts. The first, discussed above, serves to ensure that the average default rate predicted by the model equals our best estimate of the population default rate, over an economic cycle. The second part is the mapping of scores to probabilities of default, as detailed below.

The calibration curve, which maps the output of the model specified in the previous step to a probability of default, is based on analysis of the empirically observed default rate for firms with different scores[26]. In order to avoid anomalies caused by the data, the calibration curve is smoothed whilst ensuring that the tails retain their exponential nature[27]. This calibration curve is then adjusted so that the implied population default rate matches our best estimate of the anchor point default rate, 2.1%.

The process for calibrating the RiskCalc Italy model to a 5-year horizon is conceptually similar to that 1-year calibration, except that the un-smoothed calibration curve is derived using a cohort approach[28]. This curve was then smoothed and its "height" adjusted to ensure that the average predicted default rate equalled our best estimate 5-year cumulative target probability of default of 8.4%. It should be noted that we did not construct a specific 5-year model, but based the calibration on the single model developed, which was built using a mix of financial statements from between 1 and 3 years prior to default.

A problem encountered with many data sets is that there is a sample selection bias which would imply a higher default rate amongst larger companies, an implication which does not sit well with our experience and that of most experienced practitioners. Some of this bias is corrected by the fact that large firms generally have "better" financial statements, in so far as their ratios generally indicate better credit quality. However, financial statements often fail to fully capture the diversification and management sophistication benefits enjoyed by many of the larger firms, or conversely the lack of customer and/or supplier diversification and reliance on key individuals of many smaller firms.

Thus, whilst RiskCalc™ Italy predicted higher PDs for smaller firms and lower than average PDs for larger companies, it was not completely capturing the impact of these "externalities". We therefore made an adjustment to the final calibration for companies to align the predicted PDs with observed default rates. This adjustment is gradually applied to the largest firms[29], resulting in an approximate 1 ".pd" rating class improvement for the very largest firms.

To summarise, the transformation and normalisation of input ratios constitute a transparent way of capturing the information that each ratio carries about the likelihood of default. The logistic model is an efficient method of determining the optimal weights for combining the input ratios coupled with expert judgement review of the raw statistical output. Finally, the mapping transforms the model output into easily interpretable probabilities of default, which in turn are mapped to a rating grade scale[30].

Ratios And Their Relation To Default

RiskCalc™ for Italian private companies uses eight factors which fall within the following broad categories: leverage/gearing, profitability, debt coverage, activity, growth, and other/liquidity. This section provides a description of these ratios and how they have been calculated. For simplicity we have provided "names" for the ratios which capture the essence of what they measure[31].

Leverage/Gearing

Leverage is an important measure of the credit risk of a firm since it measures the firm's ability to withstand unforeseen circumstances. Within the RiskCalc™ Italy model the leverage or gearing of a firm is captured by two measures: the Tangible Net Worth ratio and the Net Indebtedness ratio.

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*26. See **Appendix D** for a fuller description of this.*

27. We have based our calibration curve on an exponential function.

*28. This involves ranking all the firms in a given year using the model, and then following their performance (i.e., default or non-default) over the following years. See **Appendix D** for a fuller description of this, and some of the issues faced in Italy.*

29. Those with turnover of more than €20m.

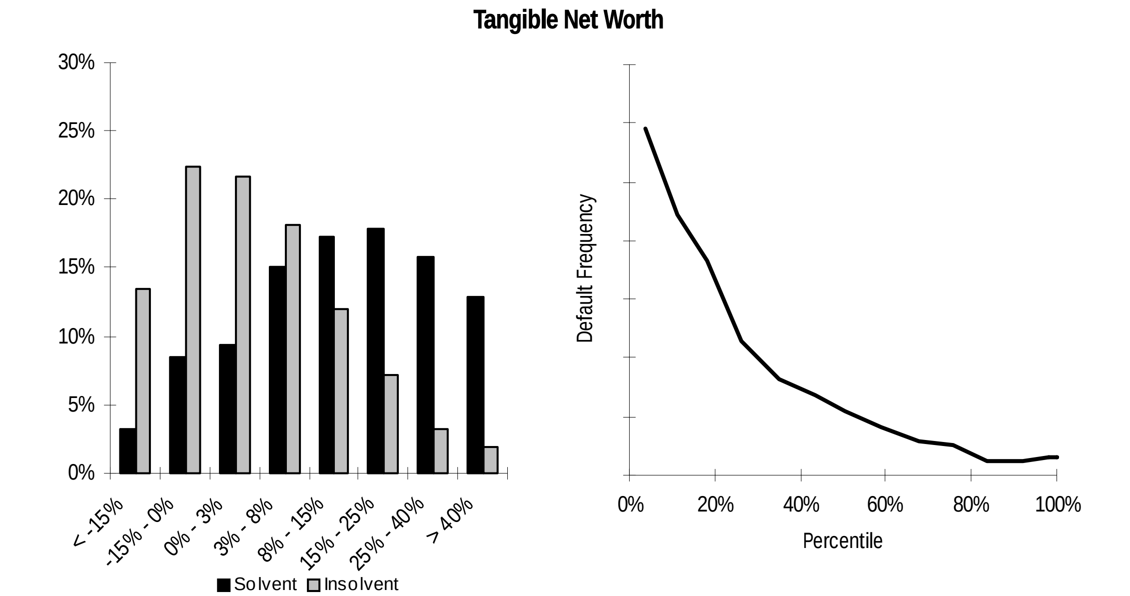
*30. See **Appendix E** for a description of the relationship between the ".pd" rating grade scale used with RiskCalc models and the widely recognised Moody's Investor Services ratings grade scale.*

*31. Precise definitions of these ratios as well as an explanation of how the ratios relate to Italian accounting standards can be found in **Appendix A***

The Tangible Net Worth ratio measures the level of a company's tangible net worth relative to its assets[32]. During development of RiskCalc Italy, it became apparent that adjusting both the Equity and the Assets positions for the value of intangible assets improved the discrimination of the ratio[33]. The ratio is an important indicator of a company's financial stability because of the ability of equity to act as a cushion in a downturn, or during a period when the company is making losses. Our initial assumption, that on average companies which subsequently defaulted had a lower level of this ratio than those which did not was confirmed by the data, as can be seen in **Figure 5**[34].

Figure 5

Firms With Lower Tangible Net Worth As A Proportion Of Total Assets Default More Frequently



The Net Indebtedness ratio quantifies the portion of a company's total debts outstanding, net of the firm's cash, relative to its total assets. This is a measure of a firm's gearing, and hence a firm's ability to withstand temporary downturns or losses. **Figure 6** below demonstrates that firms with high levels of total debts outstanding defaulted more frequently than those with low levels of net indebtedness.

32. The ratio is in defined as (Equity – Intangible Assets)/(Assets – Intangible Assets).

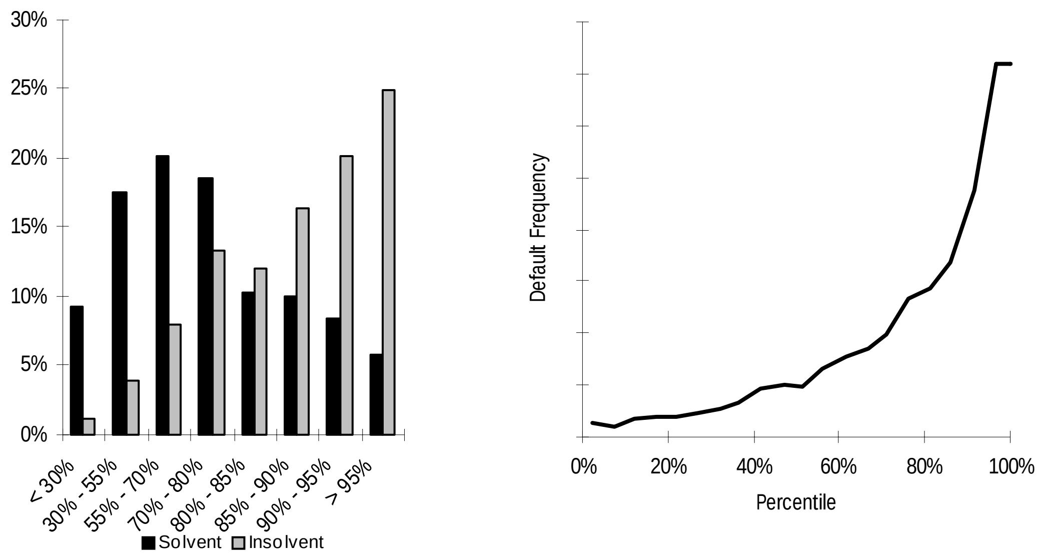
33. This probably reflects the difficulty of valuing intangible assets, and in realising value from such assets in a period of distress.

34. The figures of the relationship to default of the factors are based upon the calibration data set.

Figure 6

Firms With High Levels Of Debts Outstanding Default More Frequently

Net Indebtedness



Profitability

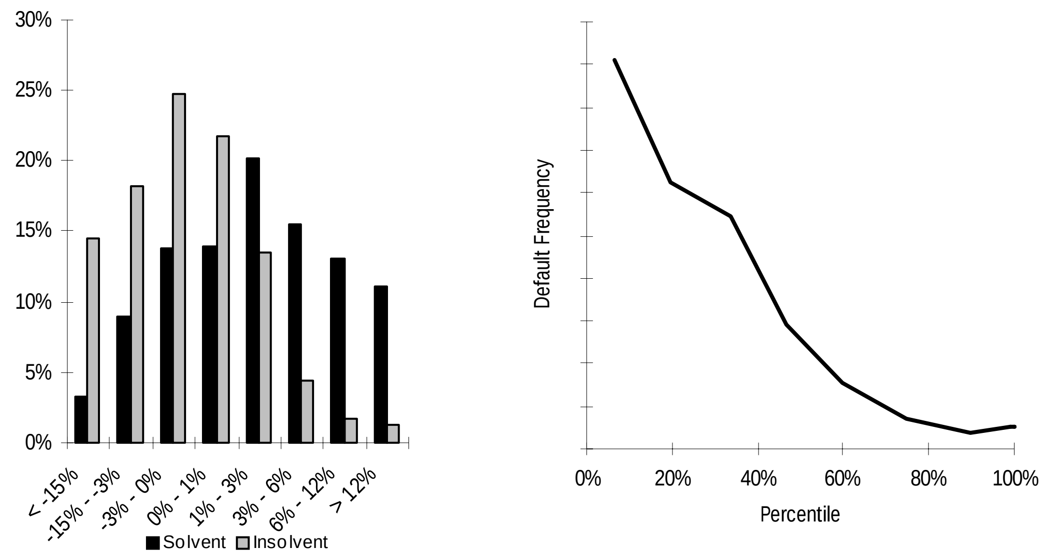
It is obvious that the future likelihood of default of a firm is dependent on its profitability since a firm which consistently makes losses will eventually become insolvent and unable to repay its debts. Furthermore, a firm with high profitability will be better positioned to withstand an interruption to its revenues and to invest in its future development. In developing RiskCalc™ Italy, we reviewed many possible measures of profitability for example Ordinary Profit Over Assets, Net Profit Over Assets, and Pre-tax Profit Over Assets. The predictive power of many of these ratios was similar and in selecting which particular ratio to use we reviewed the performance of these profitability measures in conjunction with other related measures such as debt coverage ratios[35]. Following these analyses we chose Ordinary P&L over Assets, which measures the recurring profit the firm makes before the impact of extraordinary activities or tax. Our hypothesis, that firms with lower profitability would subsequently default more frequently, was confirmed by the data as can be seen in **Figure 7**.

35. As with other factors, consideration was also given to ensuring that the selected factor was stable on different definitions of default.

Figure 7

More Profitable Firms Are Less Likely To Default

Ordinary P&L / Assets



Debt Coverage

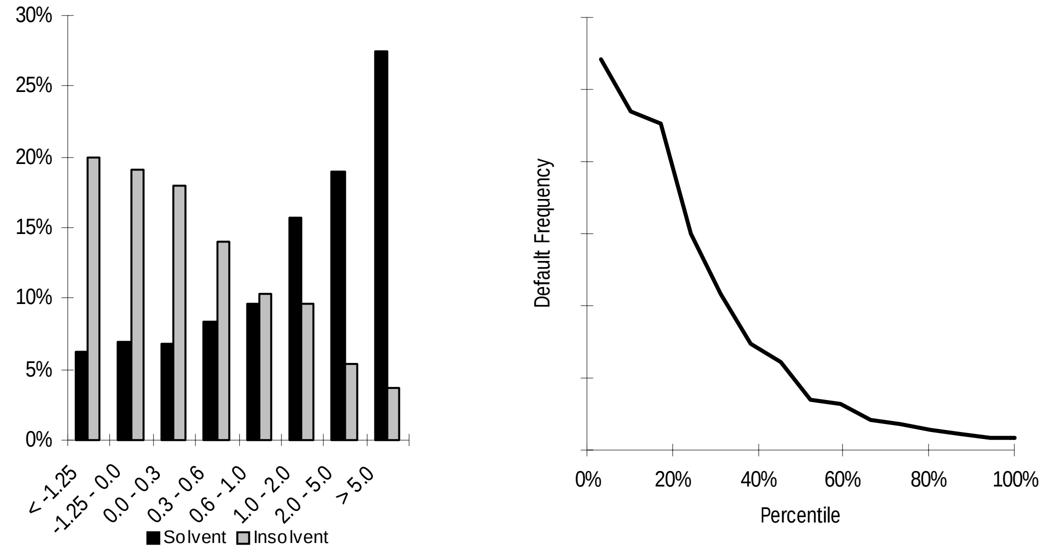
Given that the gearing and the profitability of a firm are both good predictors of firm default, it is unsurprising that debt coverage ratios, which capture both of these elements, are also good predictors. In fact BIS II proposals explicitly suggest incorporating a firm's "*capacity to generate cash to repay its debts*" within an internal rating system for corporate customers. However, there has been much discussion about what constitutes the best measure of a firm's cash flow. Given the power and importance of debt coverage ratios, we have used two ratios within RiskCalc™ for Italian private companies.

The Debt Service Coverage ratio adds the Depreciation expenses back to the Ordinary Profit, then measures this cash flow relative to a company's financial expenses. This debt service coverage ratio shows the relation between a company's Cash Flow out of its ordinary activities and its financial payments. As can be seen from **Figure 8**, those firms that are failing to generate sufficient cash flow out of their ordinary activities to cover their financial expenses tend to default more frequently.

Figure 8

Firms Who Are Able To Cover Financial Expenses From Operational Cash Flow Default Less Frequently

Debt Service Coverage

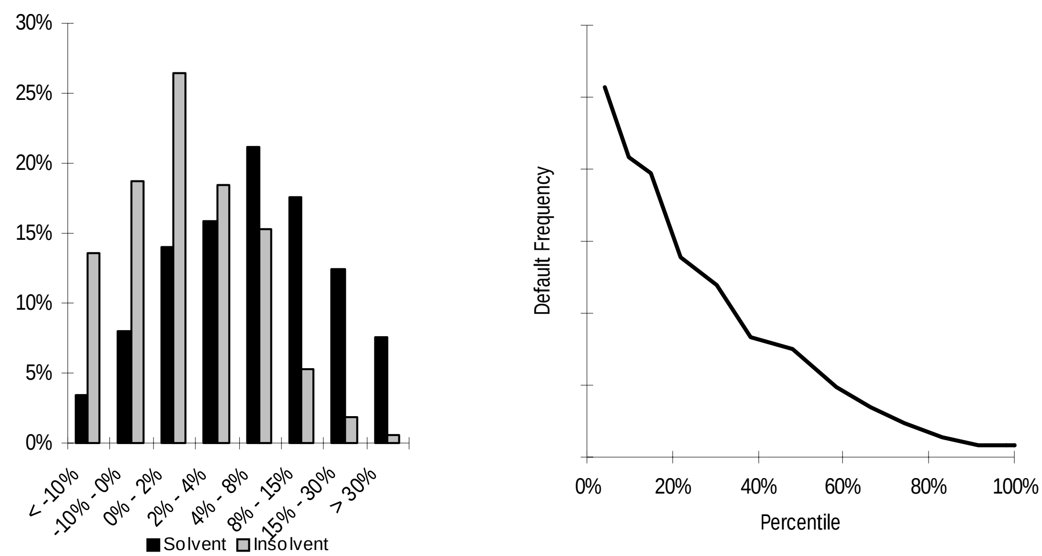


The second debt coverage ratio, Net P&L + Depreciation over Total Debts, measures the extent to which short and long-term debts could be repaid from this post-tax profits Cash Flow. As can be seen from **Figure 9**, the data strongly supported our expectation that firms with lower levels of cash flow relative to their debts would default more frequently.

Figure 9

Firms Who Are Able To Cover Debt Payments From Their Business Activities Default Less Frequently

(Net P&L + Depreciation) / Total Debt



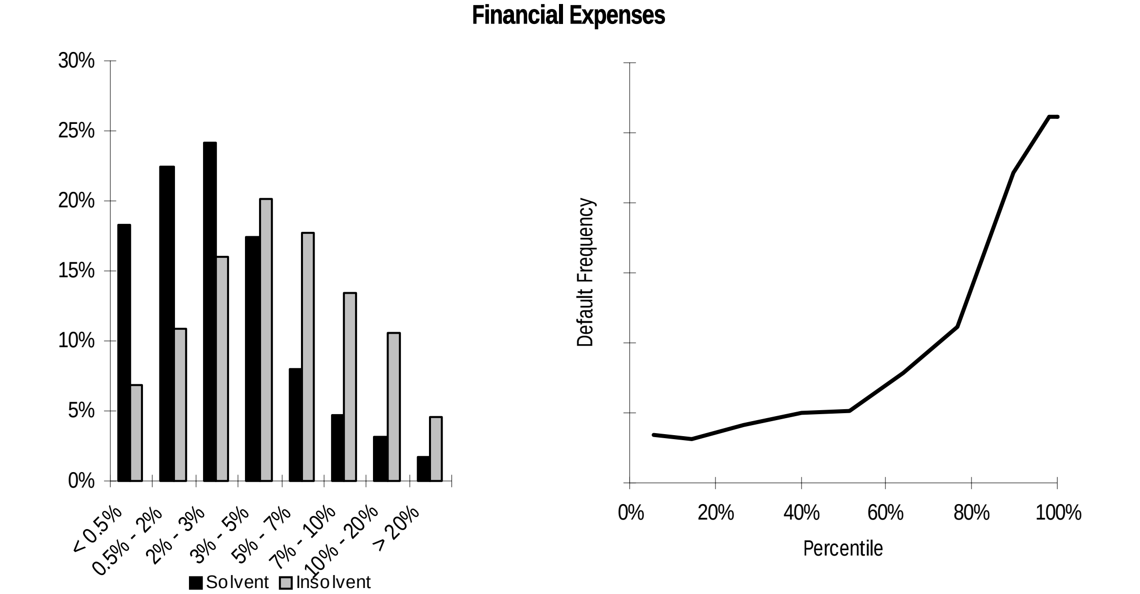
These debt coverage ratios, in combination with the profitability ratio, capture many important elements of firm profitability and its impact on a firm's probability of default: pre and post-tax measures of profitability/cash flow; principal and interest repayment capacity; the impact of reported non-recurring expenses/revenues; and the impact of possible profitability manipulation through use of depreciation and amortisation adjustments.

Activity

The Financial Expenses ratio measures the proportion of annual turnover required to repay interest expense. It is intuitively clear that, all else being equal, the higher the financing costs faced by a firm, the more likely it is to default on these payments. Also, for a given level of financial expenses, and all else being equal, a firm with higher turnover will be better able to meet its financing costs. **Figure 10** demonstrates that, as expected, firms with higher levels of interest and similar expenses relative to turnover defaulted more frequently.

Figure 10

Firms That Rely Heavily On External Funds To Sustain Normal Business Activities Are More Likely To Default



Growth

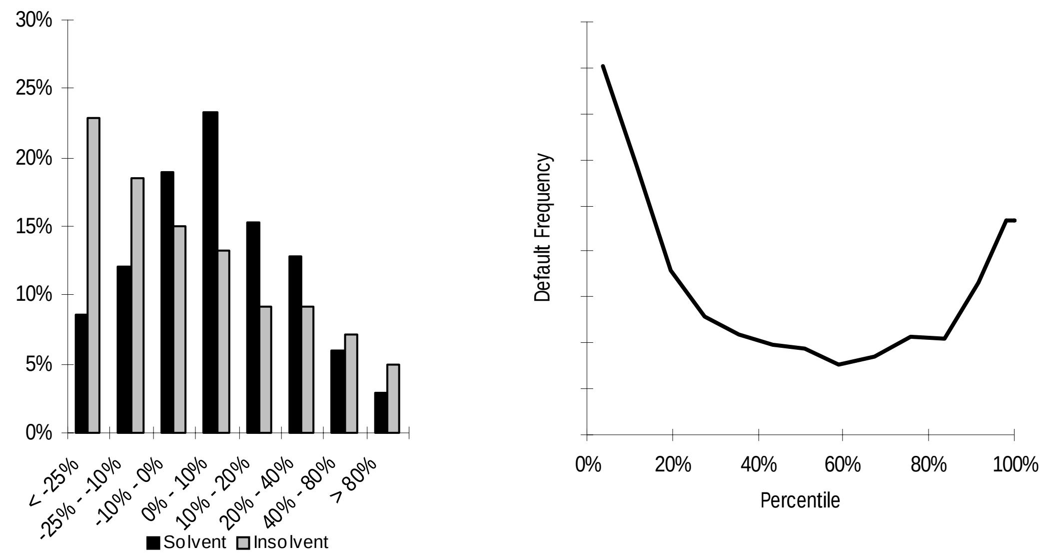
The relationship between the rate at which companies grow and the rate at which they default is not as simple as that for other ratios. The reason is that, whilst it is generally better to grow than to shrink, companies that grow very quickly often find themselves unable to meet the management challenges presented by such growth (especially amongst smaller companies). Furthermore, this growth is unlikely to be financed out of profits, resulting in a possible build up of debt and the associated risks this poses. RiskCalc™ for Italian private companies uses the most common measure of growth, a company's sales growth. Low or negative sales growth generally indicates that a firm is losing market share, or has been forced to reduce prices[36], whilst high levels can lead to the management challenges described above. As **Figure 11** shows, the relation between the Sales Growth rate and probability of default is U-shaped.

36. Clearly firms which have undergone significant restructuring, (e.g., divestments or M&A activity), could have extreme values for growth ratios. In using RiskCalc™ models, as with most other credit rating tools, it is important that the information used should be as comparable to the firm's structure in the near term as possible – thus to use a RiskCalc™ model on a firm which has recently merged, the previous year's figures should be for the merged entity.

Figure 11

Rapidly Shrinking And Expanding Firms Default More Frequently

Sales Growth



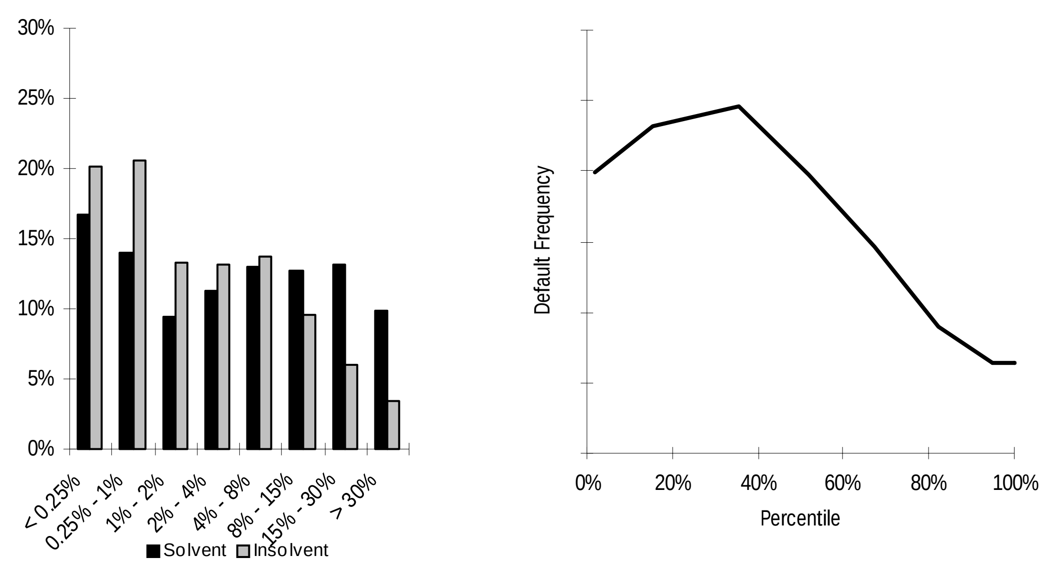
Other

Whilst the final ratio that we have included in the RiskCalc Italy rating tool, Current Asset structure, captures the liquid funds position of a firm and hence provides some measure of its liquidity, we have not classified it as a liquidity ratio. This is because in addition to measuring a firm's liquidity, it also measures the quality of a firm's current assets[37]. The quality of a firm's current assets is important, since higher quality/more liquid assets can be converted into cash more readily and at close to their market value, as opposed to lower quality/less liquid current assets such as inventories. **Figure 12** demonstrates that, as expected, firms with better quality current assets, (i.e., higher levels of liquid funds, defaulted less frequently).

Figure 12

Firms With Better "Quality" Current Assets Default Less Frequently

Current Asset Structure



37. This was supported by additional analyses which indicated both that firms which defaulted had, on average, higher levels of stocks and inventories as a proportion of assets, and that when this ratio was replaced with other possible liquidity/cash position measures, there was a deterioration in model performance.

The Weights

The output of the model is determined not only by the inputs, and hence the factor values, but also by the weights assigned to the factors. Thus, one may get a better understanding of the relation between a particular input and a particular output by looking at the weights. **Table 2** shows the relative contributions of the factors in the RiskCalc™ for Italian private companies.

Table 2

RiskCalc™ For Italian Private Companies: Relative Weights Of Risk Factor Categories

Category	Factors	Contribution
Leverage / Gearing	Tangible Net Worth Net Indebtedness	25%
Profitability	Ordinary P&L / Assets	17%
Debt Coverage	Debt Service Coverage (Net P&L + Dep.)/ Total Debts	23%
Activity	Financial Expenses / Sales	15%
Growth	Sales Growth	9%
Other	Liquid Funds / Current Assets	11%

It would be naïve to assume that the level of a firm's profitability has the same effect on its probability of default, no matter what the state of its gearing. Thus, for example, negative P&L will be much more significant for a firm with low or negative equity than for a firm with high equity. As sophisticated rating tools, RiskCalc™ models reflect this complex interaction between ratios and default. However, this can make it hard to interpret the impact any one ratio has had on the probabilities of default returned by RiskCalc™ models. To provide insight into the impact each ratio has on the PDs, results for RiskCalc™ for Italian private companies are accompanied with two additional pieces of information for each ratio: the percentile[38] in which the value for the ratio lies;[39] and the relative contribution for each ratio[40].

Empirical Tests

Historically, the primary performance measure used by academics was to assume that there was some score/cut-off below which firms were rejected (and above which they were accepted) and to then measure the percentage of misclassifications[41]. This was calculated based on the percentage of defaulting firms that were accepted, and the percentage of non-defaulting firms that were rejected, and changed depending on the cut-off selected. Essentially, power curves extend this analysis by plotting the cumulative percentage of defaults excluded at each possible cut-off point for a given model[42].

One way of interpreting the power curve is that it illustrates the percentage of defaulting firms that would be excluded as one excluded more and more of the worst "rated" firms in a data set. Thus one could interpret a power curve which went through (10%, 50%) as meaning that if one excluded the 10% of firms with the worst scores, one would exclude 50% of all firms which subsequently defaulted. In comparing the performance of two models on the same data set[43], the more powerful model will "exclude" a higher percentage of defaults for a given percentage of firms excluded (so the power curve will appear more bowed towards the top left corner of the chart).

Based on this interpretation, one can also conceive of a "perfect" model which would give all defaults worse scores than non-defaults, and a "random" or uninformative model, which would "exclude" defaults at the same rate as non-defaults. **Figure 13** shows what the power curves for a typical model, a "perfect" model and a "random" model would look like.

38. These percentiles are based on the data set which was used in calibration of the RiskCalc Italy model.

39. Of course, whether being in a top percentile is good or bad, very much depends on the ratio. Thus being in the top 5% for the Equity ratio value is good (as high equity levels are good), but being in the top 5% for the Net Indebtedness ratio is bad (since high levels of Indebtedness are bad).

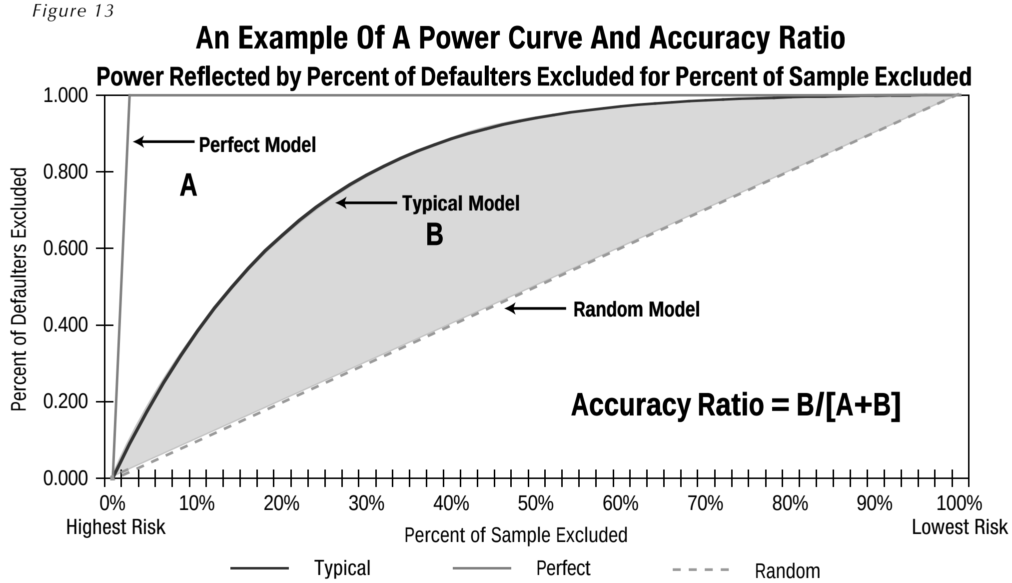
40. A discussion of the calculation of relative contributions can be found in "RiskCalc™ for Private Companies: Moody's Default Model".

41. Statistically speaking, the Type I and Type II error rates, where Type I error indicates accepting a firm which defaults, and Type II indicates rejecting a firm which does not default.

42. In fact, if you know the default rate in a sample, you can calculate the Type I and Type II error rates for a particular cut-off from the power curve.

43. It should be noted that most performance statistics are sensitive to the underlying data set and hence that a meaningful comparison can only be made between two models if the same data set is used.

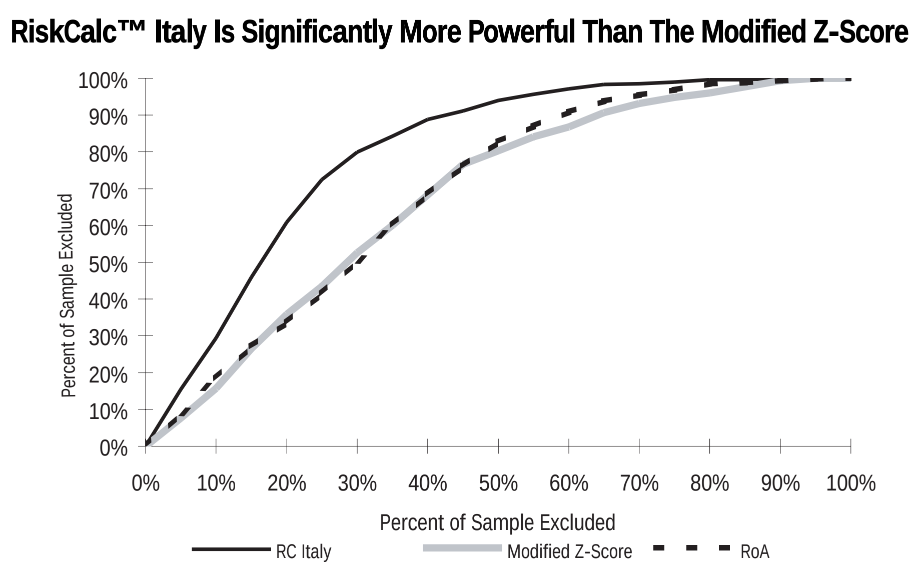
Figure 13



The accuracy ratio summarises the power curve for a model on a data set, and compares this with that of the "perfect" and "random" model. The accuracy ratio measures the area under the power curve for a model and compares this with the area under the "perfect" and "random" models, as shown in **Figure 13**, above. Thus the "perfect" model would have an accuracy ratio of 100%, and the random model would have an accuracy ratio of 0%. When comparing the performance of two models on a data set, the more powerful model on that data set will have a higher accuracy ratio.

As in development of other RiskCalc™ models, in addition to checking the absolute performance of the rating tool, we compared the performance of our tool to that of a modified version of Altman's Z-score[44], a benchmark chosen for its popularity in accounting and financial analysis texts. As one can see from **Figure 14**, the tool we developed significantly outperforms this model.

Figure 14



44. We have not used Altman's Z-score due to poor availability of retained earnings variable. We therefore used the following "model" as a proxy for the Z-score, Z = 6.56*[Working Capital/Assets] + 3.26*[Equity/Assets] + 6.72*[EBIT/Assets] + 1.05*[Net Worth/Liabilities]. We would expect this to have a similar Accuracy Ratio to the actual Z-score as we have replaced Retained Earnings / Assets by Equity / Assets, which are normally similarly powerful.*

As mentioned above, this performance across all companies can be summarised by the accuracy ratio, which measures the performance of the tool relative to the performance of a "perfect" tool. **Table 3** presents the RiskCalc™ Italy Private firm model's accuracy ratio in the "validation" sample[45], using the modified version of the Z-score and Return on Assets[46] as benchmarks[47].

Table 3

RiskCalc™ For Italian Private Companies: Accuracy Ratios

Model	Accuracy Ratio
RiskCalc™ Italy	67.6%
Z-Score	47.6%
Return On Assets	49.0%

There are a few clear messages from **Table 3**. First, the RiskCalc™ Italy Private firm model has a superior accuracy ratio, which we believe is in part due to the breadth and depth of the data set used, and to the fact that this RiskCalc model has been specifically developed for Italian firms. Second, and this is a general characteristic for the RiskCalc™ suite of models, RiskCalc™ is a significant improvement on the Z-Score benchmark.

As discussed earlier in the document, it is important when assessing the power of a tool which aims to become a market standard that the reported performance results on such a tool should be as objective as possible. The ideal situation would be to have out-of-time, out-of-sample results on which to compare performance. However, in many real-world situations such data luxuries are unavailable and an alternative approach may provide an indication of the performance of the sample.

One approach, which we have used in development of previous RiskCalc™ models, would be to use a large hold-out sample that has not been used during any part of the development. This approach requires a large number of defaults, which was not available in the present case once our database had been cleansed. However, there were still a substantial number of non-defaulting firms which were not used in development. Therefore we measured the performance of the RiskCalc™ Italy model on a data set consisting of defaulted firms used in development and non-defaulted firms which had not been used in development of the model. Our experience from previous development work, demonstrated in **Table 4**, is that accuracy ratios based on this approach are similar to those for a full hold-out sample.

Table 4

The Impact Of "Hold-Out" Sample On Accuracy Ratios*

Data Used In Development		Accuracy Ratio	
Defaults	**Non-Defaults**	**Belgium**	**UK**
Yes	Yes	73.3%	67.8%
Yes	No	73.0%	66.3%
No	No	72.5%	65.1%

** This is analysis is based on performance of a Belgian and UK model on Belgian and UK data sets respectively, and uses several hundred draws of matched numbers of defaults and non-defaults from the three different "samples". In order to avoid possible variability caused by differing time structures, we have used statements for default which occur 1 year prior to default.*

Table 5 presents the validation results of the model on sub-samples by industry, size, region, and the date of the financial statements relative to default. As shown, the model is satisfactorily stable across the different classifications. Apart from demonstrating the stability of the RiskCalc™ Italy Private firm model across industries, size groups, and regions[48], this demonstrates the fact that powerful rating tools are better at identifying firms which subsequently default as the point of default approaches.

45. This is the sample where the defaulted firms had been used in development, but where none of the non-defaulted firms had been used in development.

46. This is defined as Net P&L / Assets.

47. These accuracy ratio figures are based on using the most recent statement for a defaulting firm, provided it was available at least 24 months prior to the corporate insolvency event.

48. Here we have defined "Small" as those with turnover of less than €5m, "Medium" as those with turnover of between €5m and €25m and "Large" as all other firms.

Table 5

Accuracy Ratios For RiskCalc™ Italy By Sub-Sectors

Split	Sector	Accuracy Ratio
Industry	Construction	51.8%
Industry	Manufacturing	72.0%
Industry	Services	66.4%
Industry	Trade	64.3%
Size	Small	63.5%
Size	Medium	72.3%
Size	Large	75.0%
Date	1 year before default	72.2%
Date	2 years before default	64.6%
Date	3 years before default	58.2%

** 1, 2 and 3 years before default correspond to 18-30 months, 30-42 months and 42-54 months before the date of default of the company, respectively.*

The results in **Table 5** are based on our database of clean financial statements. **Table 6** shows how the model performs in the presence of poor quality data[49]. The sample of data used contains all statements for defaults and non-defaults which were not used in development[50], irrespective of whether they had been identified as containing poor quality information. Comparing the results in **Table 6** with those in **Table 5**, there are a couple of clear messages: RiskCalc Italy is powerful even when poor quality data is used; however, there are real benefits to having access to good quality data.

Table 6

RiskCalc™ Italy Is Still Powerful, Even In The Presence Of Poor Quality Data

Split	Sector	Accuracy Ratio
Overall		62.6%
Industry	Construction	51.8%
Industry	Manufacturing	65.8%
Industry	Services	61.2%
Industry	Trade	60.2%
Size	Small	58.6%
Size	Medium	68.0%
Size	Large	70.1%

Implementation Tips

There are a few points which one should bear in mind when using RiskCalc™ for Italian private companies. As with other RiskCalc™ models, we have not included every element that we believe impacts a firm's probability of default. For example, we have not explicitly included factors such as historical payment behaviour, management quality or considerations of a firm's position within an industry, the competitive environment in which it works and future industry outlook, even though it is commonly accepted that such factors are predictive.

Our aim in developing the RiskCalc™ suite of products is not merely to provide a set of powerful tools, but also to ensure that they can be used without imposing onerous data requirements on users. As a result we have chosen to use information that is reliable and readily available. Based only on information in the annual accounts, RiskCalc™ Italy produces very powerful results. However, prudence dictates that if one has access to additional important information one should consider it. For example, if one is aware that there are strong ties between the firm being rated and a subsidiary, and that the subsidiary is experiencing difficulties, then this information should be considered when making pricing or lending decisions. As recognised in the new Basel capital accord, being successful depends not just on having high quality information and powerful tools, but also on how these are implemented into an overall credit process.

However, as acknowledged in proposals for the new capital accord, and demonstrated by our validation results above, information contained in a firm's financial statements can prove a very powerful predictor of default. Thus we see significant scope for use of RiskCalc as the financial statement element within a credit rating system, that uses a bank's own expertise to take into account some of the non-financial elements mentioned above[51].

49. These results have been included since we feel that they are likely to be of interest to those who do not have access to high quality, or internally verified, data. These results may also be of interest to those who are considering using a commercially available financial statement database.

50. Thus it also provides a true "hold-out" sample result.

51. Moody's Risk Adviser is another Moody's KMV product which has been used by many banks to capture and combine non-financial elements within an internal rating system, and can be used to combine the outputs of RiskCalc with non-financial elements.

It is widely accepted that in using financial statement information to assess the credit-worthiness of a firm, it is desirable to use the most recent and representative information. However, whilst it may therefore be desirable to use information from interim statements, it is important to bear in mind that any P&L figures would need to be carefully annualised[52] (and that such statements are usually unaudited).

Similarly, whilst RiskCalc is powerful at a variety of horizons, and whilst we believe that using a rating based on the previous year's statement would generally be preferable to not using a rating at all, the user should consider the extent to which an older financial statement reflects the current situation of a firm. For example, if the user knows that a firm has undergone significant restructuring since publishing their last annual statement (e.g., a merger or divestiture) thoughtlessly inputting these numbers could produce misleading results. In such a case, one should aim to use the most comparable figures available.

Target For RiskCalc™ For Italian Private Companies

It is also important to bear in mind that, while we have attempted to build a robust tool which can be used on most companies, it would be inappropriate to use it on all companies. Clearly where less, or erroneous, information is available, the tool will have difficulties in differentiating how risky a firm is, but it can still be used.

The types of firm where we would recommend that users treat the results with caution are: financial institutions; public sector firms; firms whose shares are actively traded/listed; firms whose performance is dominated by a couple of specific projects (e.g., real estate development firms); firms with annual turnover of less than €500,000; and the youngest firms where the little information that is available is rarely stable or a true reflection of the status of the firm. Inaccuracies in the ratings for these firms will creep in, not only because their financial statements may not capture the whole picture, but also because the aggregate probability of default for these types of firm may well be significantly different from the population norm[53].

Conclusions

The RiskCalc™ methodology is true to the essence of applied econometrics based on sound theory and years of practical experience. The model is non-structural, well understood, and sophisticatedly simple, relying on well-established risk factors. By transforming, or "mini-modelling," the input ratios and then combining them into a multivariate model, we capture and integrate a non-linear problem, yet retain transparency. The final mapping process takes into account our "top-down" view of default rates.

We see default modelling as a forward-looking problem and so we are careful to check for robustness, both through cross-validation and out-of-sample tests, and through an emphasis on simplicity. For our Italian model, careful attention has been paid to how financial ratios could differ between Italy and other western countries considering the particularities of the Italian economy both from a micro and macro perspective. Careful attention has also been paid to how these ratios relate to default and to selecting the most parsimonious, yet robust, way to integrate them into a powerful model. The final result is a model that we believe is well tuned to forecast tomorrow's defaults, not just explain yesterday's.

Using the RiskCalc™ for Italian private companies model should help improve profitability through the credit cycle, be it through use in decisioning, pricing, monitoring or securitisation. While RiskCalc is not intended as a sufficient measure of risk, it should be viewed as a very powerful aggregator of financial statement information that generates a meaningful and validated number that allows for the consistent comparison of portfolio risks.

52. *Failure to annualise an interim statement might well lead to very poor profitability and debt coverage ratios whilst poor annualisation (e.g., simply multiplying P&L items by 4 for a quarterly statement) could be misleading in cyclical/seasonal industries.*

53. *For example, as a result of the careful regulation of financial institutions, the default rates for these firms are generally very low.*

Appendix A: Factors And Inputs For RiskCalc™ Italy

In developing RiskCalc™ models in Europe we are trying to ensure that they can be used on as wide a selection of the population as possible. This means that in selecting ratios for the final model we pay careful attention to the inputs that each ratio requires. In defining the inputs that are required for the model, we have therefore relied on account reporting regulations as a guide to the information which a user could reasonably be expected to obtain. **Table 7** shows the accounting inputs required.

Table 7

RiskCalc™ For Italian Private Companies: Model Inputs

	Line items, English	Line items, Italian
Balance Sheet, Assets	Intangible Fixed Assets	Totale Immobilizzazioni Immateriali
	Liquid Funds	Totale Dispon. Liquide
	Current Assets	Totale Attivo Circolante
	Total Assets	Totale Attivo
Balance Sheet, Liabilities	Shareholders' Equity	Totale Patrimonio Netto
	Total Debts	Totale Debiti
Profit And Loss	Revenues from the Sale of Goods and Services (t)	Ricavi delle vendite (t)
	Revenues from the Sale of Goods and Services (t-1)*	Ricavi delle vendite (t-1)
	Total Value of Production	Totale Valore della Produzione
	Depreciation of Tangible Fixed Assets	Ammortamenti e svalut: Immobilizzazioni materiali
	Amortisation of Intangible Fixed Assets	Ammortamenti e svalut: Immobilizzazioni immateriali
	Costs and Expenses for Production	Totale Costi Produzione
	Interests and Other Financial Expenses	Totale Oneri Finanzieri
	Financial Income and Expense	Saldo Proventi e Oneri Finanziari
	Profit (loss) after Taxation	Risultato Esercizio

** Here (t-1) indicates the previous fiscal year.*

Table 8 shows how these line items are combined to create the accounting concepts used within RiskCalc™ Italy (we have only included an item in this table if it is not a clearly defined input).

Table 8

RiskCalc™ For Italian Private Companies: Inputs And Accounting Concepts

Concept	Calculation From Inputs
Sales	Revenues from the Sale of Goods and Services
Depreciation	Depreciation of Tangible Fixed Assets + Amortisation of Intangible Fixed Assets
Ordinary P&L	Total Value of Production – Costs and Expenses for Production + Financial Income and Expenses
Net P&L	Profit (loss) after Taxation

Table 9 shows how these line items are combined to create the ratios used within RiskCalc™ Italy.

Table 9

RiskCalc™ For Italian Private Companies: Ratio Calculations

Category	Name	Definition
Leverage/ Gearing	Tangible Net Worth	(Shareholders' Equity – Intangible Fixed Assets) / (Total Assets - Intangible Fixed Assets)
	Net Indebtedness	(Total Debts - Liquid Funds) / Total Assets
Profitability	Ordinary P&L / Assets	Ordinary P&L / Total Assets
Debt Coverage	Debt Service Coverage	(Ordinary P&L + Depreciation)/ Interests and Other Financial Expenses
	(Net P&L + Depreciation) / Total Debts	(Net P&L + Depreciation) / Total Debts
Activity	Financial Expenses/ Sales	Interests and Other Financial Expenses/ Sales
Growth	Sales Growth	[Sales (t) - Sales (t-1)]/ Sales (t-1)
Other	Current Assets Structure	Liquid Funds / Current Assets

Appendix B: The Logistic Model

When analysing the explanatory power of variables in a multivariate context, we combine them in a logistic model. Its main advantages are that it handles dichotomous (yes/no) dependent variables (in this case default/non-default) and, through the use of the logistic function, maps scores to values between 0 and 1, which correspond to probabilities of default.

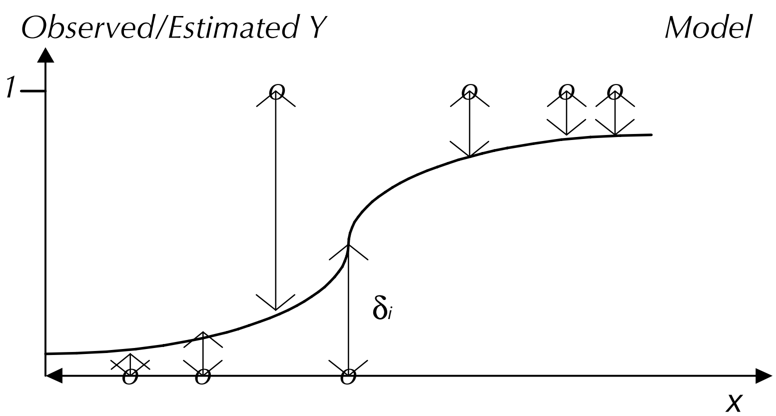
In particular, the model estimates the relationship between the transformed variables and the default/non-default flags by a *transformation* of a linear combination of independent variables. The model is of the form:

$$Y = \frac{exp(\alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \ldots\ldots + \alpha_v X_v)}{1 + exp(\alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \ldots\ldots + \alpha_v X_v)} \qquad (A.1)$$

where, Y is the dependent variable (i.e., the default/non-default flag) and, X_i are the independent variables (i.e. the transformed, normalised financial factor scores). The observed value of Y is either 0 (not defaulted) or 1 (defaulted), whereas the calculated Y can be any value between 0 and 1. This model, as shown in **Figure 15** for the case of a model with one independent variable, is S-shaped.

Figure 15

The Logistic Model Is S-Shaped



To our mind, the S-shaped nature of this function is a good reflection of the underlying reality: clearly there comes a point where, for example, increasing losses has little additional impact upon a firm's probability of default; similarly, if a firm has excellent gearing, debt coverage, and profitability ratios, then a small decrease in the level of sales should have little impact on its probability of default. A linear model, unlike a logistic or probit model, does not capture these effects, but forces the same change in probability of default for a given change in a ratio, irrespective of the overall level of this ratio, or the values of the other ratios.

In optimising the selection of weights, a statistical package will adjust the parameters, α_i to minimise the error between the observed and predicted values of y (i.e., the δ_i in **Figure 15**). This is done by minimising the loss function, which in this case is the sum of all $\ln(Y_{predicted})$ for defaulted customers minus the sum of all $\ln(1\text{-}Y_{predicted})$ for healthy customers, i.e.,

$$Loss = \sum((Y_{observed})ln(Y_{predicted}) - (1 - Y_{observed})ln(1 - Y_{predicted})) \qquad (A.2)$$

Appendix C: Testing Metrics

Power Curves

A power curve[54] is constructed by plotting, for each score, *m*, the proportion of *defaults* with a score worse than[55] *m*, against the proportion of *all* firms with a score worse than *m*. In order to plot the power curve for a model, one should do the following:

- Score all the firms with the model.
- For each score, *m*, calculate the percentage of *all* firms with scores worse than *m* — this is the x-axis value[56].
- For each score, *m*, calculate the percentage of *defaulted* firms with scores worse than *m* — this is the y-axis value.

Thus, if a particular model or metric *M*, gave 5% of all firms a score worse than *m*, and 10% of all defaults a score worse than *m*, then its power curve would go through the point (0.05,0.1). This could be interpreted as meaning that if one were to reject all credits with a score in the worst 5% (based on *M*), then one would exclude 10% of all firms who go on to default.

If we consider a particular metric *M*, for which we bucket the scores into *B* different bins, then the height of the power curve in a particular bin, *b*, would be calculated as follows:

$$power\ (b) = \frac{\sum_{i=1}^{b} D(i)}{\sum_{i=1}^{B} D(i)} = \frac{defaults\ excluded\ at\ b}{total\ defaults} \qquad (A.3)$$

where, *power(b)* is the height of the power curve in bin *b* and *D(b)* is the number of defaults in bin *b*.

The result is **Figure 16** below which plots the power curve for a metric *M* (the line *power(M)*, which relates to the left hand axis). In this case we rank-order the firms from risky (left) to less risky (right). This model would quickly have "excluded" most of the bad companies: a 20% exclusion of the worst companies according to the *M* score would exclude 70% of the future defaulters.

Figure 16

Power Curve And Calibration Curve

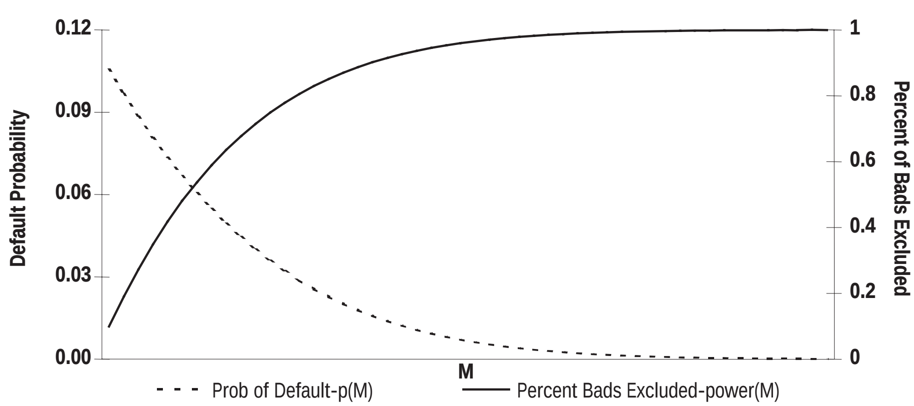


Figure 16 also demonstrates the fact that a power curve, together with a default rate, implies a particular calibration curve (this is plotted as Calib(M) which relates to the right hand axis). The default rate for a particular percentile, is equal to the slope of the power curve at that point, multiplied by the average default rate for the sample. Thus, for any point m along a default metric:

$$Calib(m)\ \ p(t) = \overline{p} * \frac{\partial\ power\ (m)}{\partial m}, \qquad (A.4)$$

where $\bar{p}$ is the mean probability of default, and $\frac{\partial Power(m)}{\partial m}$ is the slope of the power curve at point *m*.

---

54. Also known as a CAP plot.
55. Here "worse than" is taken to indicate that the firm is higher risk, (i.e., more likely to default).
56. We use percentage on the x-axis rather than the score output so that two models, with possibly different ranges of scores, can be compared to one another on the same data set.

Accuracy Ratio

While the graphical or tabular display of power is informative, and has the advantage of allowing one to examine power at a variety of thresholds, it is useful to aggregate the power curve information into a single number that allows unambiguous comparison. The metric that we use, called the Accuracy Ratio, compares the area under the power curve for the model with the area under the random and perfect models. A more powerful model will be bowed out towards the left, and will have a larger area, resulting in a higher accuracy ratio.

The accuracy ratio is defined as the ratio of the area between the actual model and the random model to the area between the perfect model and the random model (see Figure 13 in the Empirical Tests section for a graphical demonstration). Thus the perfect model would have an accuracy ratio of 100% and a random model would have an accuracy ratio of 0%.

Using the area under the power curve implies that there can exist threshold levels such that a model with a smaller total area has a momentary advantage. Thus the accuracy ratio is not a measure of global or complete dominance, just an intuitive measure of dominance on average.

It should be noted that it would be inappropriate to compare the accuracy ratios for two models on two different data sets, since any model tested on two different data sets will get different accuracy ratios on the data sets. The accuracy ratio does however allow one to compare the performance of two models on the same underlying data set.

Appendix D: Calibration Curve Construction Details

The model was calibrated to a one-year and a cumulative five-year horizon. In constructing the one year calibration curve, we want to use the most up-to-date information which would have been available in time to be of use to someone making a credit decision. Thus in selecting statements for firms which subsequently defaulted, we excluded those which were "too close" to the point of default.

The first step in determining which statements are "too close" is to account for the fact that there will be a time lag between when an expectation of credit loss would have occurred, and the reported date of insolvency[57]. This time lag is especially significant in Italy, where bankruptcy proceedings start very late. To account for this lag between default and insolvency, we allowed a minimum 12-month lag between the date of the statement and the date of insolvency. Since we want to predict the default event a year in advance, the second step is to ensure that the period covered by the statement ended at least 12 months prior to the point at which one would have an expectation of a credit loss. Thus we excluded all statements whose closing date was within 24 months of the reported insolvency date. We then selected the most recent statement for a firm, although, if there was no statement in the previous 24 months, then we excluded the firm.

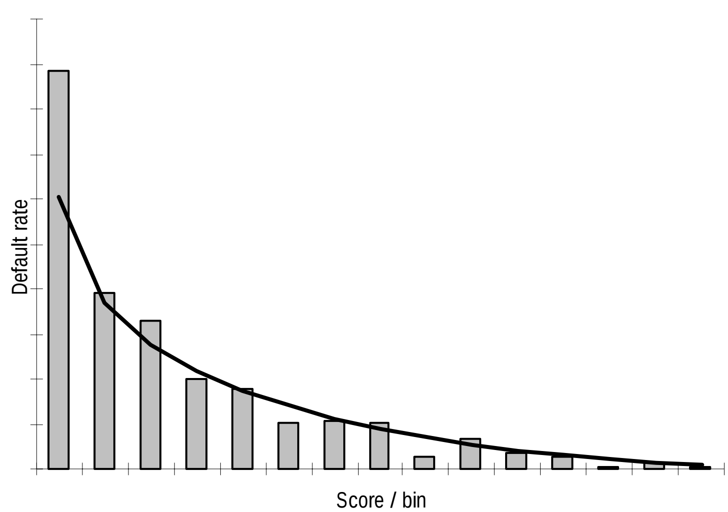
Thus for each defaulting firm, we selected the most recent statement between 24 and 47 months prior to the insolvency date and calculated its score. Where no statement was available in this 24 to 47 month period, we excluded the observation. For example, if a firm had defaulted on October 1st 1999, we would have excluded any statements which closed in the previous 24 months, (i.e., after September 1997). We would then have used the most recent statement from the period between September 1997 and October 1995, and calculated the score based on this statement. If no statement was available from this period, then the default would have been excluded.

Having calculated a score for defaulted firms, we also calculated scores for firms which did not default. The scores for defaulted and non-defaulted firms were then assigned to score "bins,"[58] and a default rate was calculated for each bin[59].

This is the observed calibration "curve" (the bars in **Figure 17**), which is then smoothed to overcome data anomalies and relate a score to a default rate (the curve in **Figure 17**). The "height", or intersect with the y-axis, of this curve is then adjusted[60] to ensure that the predicted default rate across our whole portfolio reflects the aggregate probability of default assumption.

Figure 17

The Observed Default Rate For Different Scores Is Smoothed During Calibration



57. As previously mentioned, whilst the default flags which we have within our database are based upon a corporate insolvency definition of default, in calibrating the model, we are trying to predict a typically earlier event, more akin to a bank definition of default.

58. These bins can either be defined so as to ensure that they contain the same number of statements, or they can be defined so that the score "cut-offs" are evenly spaced (although this can lead to some bins containing very few points).

59. The default rate is calculated as the number of statements for firms in a given bin which subsequently defaulted, divided by the total number of statements within that bin.

60. This adjustment doesn't affect the relative risk of firms. Thus, if the PD for firm A was twice that of firm B before the "height" adjustment, then after the "height" adjustment, the PD of firm A will still be twice that of firm B.

As mentioned above, the five-year calibration curve was constructed using a cohort approach. In the cohort approach, the model is used to score all statements for all firms in a given year, and these firms are tracked for the next *n* years to see which firms defaulted[61]. These results are then used to construct a score bin and calculate a default rate for each score bin, as in the 1 year calibration. This "curve" is then smoothed and adjusted in order to ensure that the average predicted default rate across our whole portfolio reflects the aggregate probability of default assumption.

Thus to construct a 3 year cohort based on financial statements from 1995, one would use the model to score all firms with statements in 1995, and then track their performance over the next 3 years, to identify whether any defaulted in that period. If a firm defaulted during the 3 year period then it would be identified as a default, otherwise it would be treated as a non-defaulting firm. One would then construct score "bins", calculate the default rate in each "bin", and then fit a curve to smooth the observed data, adjusting the curve in order to ensure that the average predicted PD is appropriate.

In an ideal situation, one would have a number of 5-year cohorts which could then be used to derive the calibration curve. Unfortunately, we were unable to do this for the RiskCalc Italy model, and have had to rely on an analysis of the drop in power of the RiskCalc Italy model as one moves from a 1 year prediction horizon to more distant prediction horizons[62]. These results, based on 1 to 4 year cohorts calculated using our Italian data set, were compared with our experience in developing other RiskCalc models, where we had a number of 5-year cohorts available. This analysis allowed us to select a calibration curve with an appropriate slope.

61. Again we allowed a 12 month lag between our default definition and when we believe the expectation of a credit loss would occur, and we allowed approximately 6 months to ensure that the statement would have been available.

62. As mentioned in the ***Empirical Tests*** *section, one generally expects to see a drop in performance as one attempts to predict more distant defaults with a given financial statement. This drop in power leads to a calibration curve which is less "steep" than the 1 year calibration curve, (i.e., the ratio between the highest predicted PD and the lowest predicted PD is lower).*

Appendix E: The Relation Between RiskCalc PDs And Dot-PD Ratings And Moody's Investor Services Long-Term Bond Ratings

RiskCalc PDs and Moody's long-term bond ratings are not directly comparable. They are two different, though related, credit risk measures. **Exhibit 1** compares many aspects of the two systems side-by-side, highlighting similarities and differences.

Exhibit 1

Similarities & Differences Between RiskCalc PDs And Moody's Long-Term Bond Ratings

Characteristic	RiskCalc PDs	Moody's Long-Term Bond Ratings
Unit of Study	Obligor	Obligation and/or Obligor
Time Horizon	Specific, one or five years	Non-specific, long term
Risk Dimension	One dimensional: Probability of default	Multi-dimensional: Probability of default, severity of default & transition risk
Information Requirements	Large, reliable, electronic datasets	Robust to poor quality or missing data
Volatility	High	Low - maintained through the cycle
Cost	Low	High
Support	Technical	Technical + Analyst contact & insight
Scale	Continuous/Absolute	21 Risk Buckets/Relative
Structure	Simple, codified analysis of few variables	Flexible as situation may require

Despite the important differences between RiskCalc PDs and Moody's long-term bond ratings, some users of one or both risk nomenclatures find it helpful to compare them. Moody's bond default study provides a basis for such a comparison. This study rigorously correlates Moody's long-term corporate bond ratings with ex-post default frequency, allowing us to calculate historical average bond default rates for each rating category. By mapping a firm's PD into the historical average bond default rates, we create dot-PD ratings (e.g., Aaa.pd, Aa1.pd, Aa2.pd, …, Caa2.pd, Caa3.pd, Ca.pd, C.pd), which facilitate comparison with long-term bond ratings. Moody's bond default study is available over Moody's KMV's web site at ***http://www.moodyskmv.com***. The details of the PD mapping to historical average long-term bond default rates are described in the May 2000 Special Comment, "Moody's Default Model for Private Firms: RiskCalc for Private Firms," also available from the web site.

Dot-PD ratings carry no additional information beyond PDs and are not long-term bond ratings for all of the reasons highlighted in **Exhibit 1**. They are, rather, a re-statement of the PDs and provide a shorthand nomenclature for probabilities of default. Our clients have found that, for some purposes, communicating risk levels in terms of alpha-numeric, ratings rather than probabilities, is more intuitive. For example, for many, the difference between two companies with 0.0075 and 0.0131 probabilities of default is not as easily understood as the difference between an A3.pd company and a Baa1.pd company.

While dot-pd ratings are not the same as long-term bond ratings, there is a correlation between them. The correlation, *by construction*, is not exact. Ratings, as indicated in Exhibit 1, are functions of not only PD, but also of the severity of loss in the event of default (which incorporates key structural differences in instruments such as senior vs. subordinate, secured vs. unsecured, external supports) and an issuer's risk of sudden, large changes in credit quality. Moody's bond default study correlates ratings with only one of these risk dimensions, probability of default, while holding constant the severity of loss and ignoring transition risk. For this reason, by construction, the correlation between the two systems is imprecise.

An analogous situation is the relationship between a person's weight to their height and girth. There is a strong enough correlation between weight and height that we may draw the conclusion that taller people, on average, weigh more than shorter people. However, we could more accurately predict weight if we knew not only height but also girth. Analogously, we could more accurately predict Moody's bond ratings if, in addition to PD, we know the severity of loss[63], the transition risk, and the other differences outlined in **Exhibit 1**.

The intent of Moody's RiskCalc models is not to substitute or predict Moody's bond ratings. They are designed to calculate expected probabilities of default for defined time horizons. The output of these models, combined with correlation estimates, will facilitate quantification of risk at the obligor and portfolio level.

In contrast to PDs, which are produced by a formula that relates information in selected financial ratios to probabilities of default, Moody's analyst ratings are based on a more flexible and focused review of qualitative and quantitative factors, distilled by an analyst (and rating committee) with sectoral expertise and in-depth understanding of an issuer's competitive position and strategic direction.

Despite the structural difficulties in directly comparing PDs with long-term bond ratings, many of our customers will find the systems complementary and valuable in different ways as part of a risk management solution.

63. The severity of loss can be captured through use of LossCalc, another Moody's KMV product which provides a measure of the expected loss in the event of default.

Rating Methodology

Moody's RiskCalc™ For Private Companies: Italy

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