July 2002

Moody's RiskCalc™ For Private Companies: Portugal

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 Portugal joins RiskCalc™ private firm models for the US, Canada, Australia, Germany, Spain, France, UK, Mexico, Japan and Belgium and a US bank model, allowing one to consistently attach probabilities of default to private firms throughout the world. 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 Portuguese private companies
• A description of the methodology used to develop the model,
• A comparison of the relationship of various financial ratios to default, and
• 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 Portuguese 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 website www.moodyskmv.com

Contact

<table>
<thead>
<tr>
<th>New York</th>
<th>Phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ahmet E. Kocagil</td>
<td>1.212.553.1653</td>
</tr>
<tr>
<td>David Bren</td>
<td></td>
</tr>
<tr>
<td>London</td>
<td></td>
</tr>
<tr>
<td>Anna Wingate</td>
<td>44.20.7772.5454</td>
</tr>
<tr>
<td>David Wright</td>
<td></td>
</tr>
</tbody>
</table>
Introduction

Experience has shown that a key determinant of lending performance is the ability to correctly assess 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. **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. **Calibrated to probabilities of default (PDs), and** 
   While an un-calibrated model 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. **Empirically validated.** 
   Without documented performance on large datasets, prudence dictates that a third-party model must be viewed sceptically\(^2\). Such testing also gives the user confidence that the model is stable and has not been “overfitted”\(^3\).

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 Portugal 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 Portuguese private companies\(^4\) has been developed in co-operation 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. We have been in the fortunate position that a RiskCalc Sponsor bank has validated the performance of the model on their data. The intention is to publish the results of their testing, together with testing by other sponsor banks of RiskCalc models, later in the year.

3. Of course, the level of validation that can be performed depends on the amount of data, which is available. For example, Ireland has a relatively small economy, has enjoyed a prolonged economic boom and has historically had poor financial statement reporting compliance, all of which would combine to reduce the amount of information available for model validation.

4. By “private firm” we refer to those firms who do not have publicly quoted and traded equity.
Data Description

The intention with 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 Portuguese private companies is to provide a probability of default (PD) for private Portuguese companies with annual turnover\(^5\) of more than €500,000\(^6\). 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:

- **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 annual 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 to 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\(^7\). For this reason pure real-estate development companies were excluded from development.

- **Public sector institutions** – rating public sector companies is complicated by the fact that the states or municipalities which use/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.

Table 1 provides a summary of the data set used in development, validation and calibration of RiskCalc™ for Portuguese private companies and compares it with those used in developing other RiskCalc™ models. Unlike previous model developments the data which was available was limited, although sufficient to allow development of a robust model. This was driven by the size of the Portuguese economy\(^8\) and a weak account reporting culture\(^9\).

<table>
<thead>
<tr>
<th>Country</th>
<th>Time Span</th>
<th>Unique Firms</th>
<th>Unique Firm Defaults</th>
<th>Financial Statements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portugal</td>
<td>1993-2000</td>
<td>18,137</td>
<td>416</td>
<td>69,765</td>
</tr>
<tr>
<td>Belgium</td>
<td>1992-1998</td>
<td>102,594</td>
<td>6,658</td>
<td>523,057</td>
</tr>
<tr>
<td>UK</td>
<td>1989-2000</td>
<td>64,531</td>
<td>4,723</td>
<td>283,511</td>
</tr>
<tr>
<td>Spain</td>
<td>1992-1999</td>
<td>140,790</td>
<td>2,265</td>
<td>569,181</td>
</tr>
<tr>
<td>United States</td>
<td>1989-1999</td>
<td>33,964</td>
<td>1,393</td>
<td>139,060</td>
</tr>
</tbody>
</table>

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™ Portugal data set and the data sets available in other countries.

---

3. This includes revenue both from sales of goods and merchandise and from services rendered.

6. 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.

7. 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.

8. Portugal accounts for less than 2% of European GDP.

9. Whilst Portuguese reporting requirements are similar to those in other countries, penalties for noncompliance with these have historically been limited.
Figure 2 demonstrates that even after excluding the very smallest firms\textsuperscript{10} from our database, the number of financial statements is dominated by firms which have annual turnover of less than €1 million. This effect is common in much of Europe with the total number of firms dominated by the smallest firms.

Figure 3 shows that the database used in developing, validating and calibrating RiskCalc\textsuperscript{TM} Portugal had a similar distribution across industries as the database used in developing the RiskCalc Spain model\textsuperscript{11}.

\textsuperscript{10} Those with turnover of less than €500,000.
\textsuperscript{11} Readers are referred to other RiskCalc\textsuperscript{TM} documents for the industry distributions of the databases used in developing other RiskCalc\textsuperscript{TM} models.
Definition Of Default
Our intention in developing RiskCalc™ for Portuguese 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 is widely used in Portugal, this is considered inappropriate in other countries, for example Italy, or in certain sectors such as public sector entities.

One of the aims of the RiskCalc™ suite of products is to provide a market benchmark for comparing the probability of firm default not only within a country, but also to allow meaningful comparison across countries. 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 banker’s 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, 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 or bankruptcy.

The development of RiskCalc™ for Portuguese private companies is similar to the development of RiskCalc™ US in that, in developing the first version of the model for Portuguese private companies, we have used a “90 days past due” definition of default for identifying and modelling the key indicators of credit losses. The definition of default targeted when calibrating the RiskCalc™ model for Portuguese private companies is described in the following section.

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. In Portugal our discussions with the sponsor bank suggested that this would occur around the 90 days past-due point.

The estimate of an aggregate probability of default is important because it serves as an anchor point for the model. Changing it upward 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 Portuguese firms, would have a very different anchor point PD than 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.

12. 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.

13. Of course the seriousness of being 90 days past due not only depends on the country, or client type, but also on the instrument, for example a firm which was 1 day past due on a capital market transaction or bond repayment would be considered in default. Furthermore, where a debt holder has match funded debt, a firm which is overdue for any period will force some costs onto the debt holder (since they would be forced to seek alternative financing for the period during which payment is overdue).

14. 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.
In addition to considerations about size, legal form and industry 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\(^{15}\) (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.

As part of its commitment to developing the RiskCalc\(^{TM}\) suite of products, Moody’s KMV has formed a RiskCalc\(^{TM}\) Sponsor Group consisting, at the time of writing, of nine major European financial institutions from six European countries. One of the benefits of these relationships is that it has allowed us access to portfolio level bank default experience in Portugal\(^{16}\). This access has enabled us to verify the robustness of our central tendency estimate for the model\(^{17}\).

In addition to this aggregate sponsor bank default data, we analysed Portuguese bank’s loan loss provisions, which, over time, will tend to equal actual losses and hence reflect the underlying bank default rate. Loss rates and default rates are tied together by the loss given default rate (LGD) using the following formula:

\[
\text{Volume of Losses} = \text{Volume of Loans} \times \text{Probability of default} \times \text{LGD}
\]

\[
\Rightarrow \quad \text{Probability of Default} = \frac{\text{Volume of Losses}}{\text{Volume of Loans} \times \text{LGD}}
\]

In deriving a PD from a provisioning based figure, it is also important to bear in mind the fact that the result is volume based. Thus, the result is driven by banks’ exposure to the largest firms.

Based on these different sources and the considerations outlined above, we have used an anchor point of 1.5% for the 1 year PD in calibrating RiskCalc\(^{TM}\) Portugal.

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\(^{18}\) 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\(^{19}\), approximately 4 times the level of the 1 year default rate. Thus in calibrating RiskCalc\(^{TM}\) model for Portuguese private companies for the 5 year horizon, we have used an anchor point of 6%.

**Model Description**

RiskCalc\(^{TM}\) for Portuguese 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 KMV and Oliver, Wyman and 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\(^{20}\). 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 \textit{a priori} as independent variables in the final model. In this step we also mini-model the factors.

---

15. This assumes that there has not been a structural shift in default rates, e.g. in the US, post the oil shocks.
16. The initial press release (dated October 18th 2001) announcing the formation of the RiskCalc\(^{TM}\) Sponsor Group, which contains a list of the institutions involved in the RiskCalc\(^{TM}\) Sponsor group, can be found on the Moody’s web site. The intention is to increase the size of the sponsor group and so the interested reader should look for other announcements.
17. For those unfamiliar with calibration, it is worth noting that the aggregate default rate used in calibration should reflect the scope of the database used during development of a rating tool and intended use of a rating tool. Thus the central tendency used in calibrating a rating tool for use on very small firms should be very different to that used in calibrating a rating tool for use only on the very largest firms.
18. For more details on this work, we refer the reader to the description in “RiskCalc\(^{TM}\) For Private Companies: Moody’s Default Model”.
19. 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.
20. 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).
• 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, it is necessary to map the output of the model, a score, to a specific 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 in very different ways 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 regressors, those factors that have a high discriminatory power between defaulted and non-defaulted companies.

• 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 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 to capture their relationship to default. As shown in Figure 4, 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. Interest & Similar Expenses / Turnover), or always negative, so that a lower ratio value indicates a higher probability of default (e.g. Equity / Accounts Payable). It is also apparent from Figure 4 that this relationship is generally not a straight line relationship (i.e. it is “non-linear”).

21. 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.

22. For more details, 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.

23. 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 gearing measure, Equity / Accounts Payable that higher gearing levels (i.e. lower levels of equity) are associated with higher default rates. These two graphs are similar to the graphs shown on the right hand side of Figures 5-10.

24. The most widely documented class of non-monotonic ratios is growth ratios, which often exhibit a U shaped relation with default.
Given this monotonicity we model the relationship to default so that we capture it in a smooth manner and “cap” extreme values. This “capping” not only eliminates the impact of outliers in the estimation of the parameters of the final model, but ensures that the final ratings awarded to a firm are not distorted by the impact of a small number of observations. 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 of 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 sub-samples, ensuring that the weights for the factor category (e.g. debt coverage) are stable, before splitting the category weight between the ratios in the category.

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 most likely have onerous data input requirements. When deciding on the final model to use, we combined an analysis of the power of the different models, as measured by the accuracy ratio, with our experience. Some of the considerations that went into the selection of the final ratios and model are:

- 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,
- the model should have high explanatory power

---

25. As part of the is 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.

26. Thus, for example we estimated weights for a model including only Cash Flow / Liabilities, and for a model with only Debt service coverage, 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.

27. 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. As the size of a development data set decreases the confidence one has about the significance of factors selected by a statistical procedure also decreases.
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 will equal our best estimate of the average population default rate, over an economic cycle. The second part is the mapping of scores to probabilities of default, as detailed below.

The basic methodology for generating the 1-year calibration curve was the same as the approach adopted in other RiskCalc models, where the overall sample is used to create a calibration curve (which maps a score to a PD)\(^28\). In order to avoid anomalies caused by the data, the calibration curve is smoothed whilst ensuring that the tails retain their exponential nature\(^29\). This calibration curve is then adjusted so that the implied population default rate matches our best estimate of the anchor point default rate, 1.5%.

In deriving the calibration curve for the cumulative five-year horizon, we constructed a 5 year cohort\(^30\) based on the 1995 data. Since it is harder to identify those firms which will default during the next 5 years (rather than just within the next year), the calibration curve for a cumulative 5 year prediction is generally less steep than for a 1 year horizon\(^31\). In order to ensure that the calibration curve was not too steep, we compared the change in slope of the calibration curve moving from a 1 year to a 5 year horizon, with the change observed for RiskCalc models in other countries where we had more data.

This calibration curve was then smoothed and its “height” adjusted to ensure that the predicted default rates equalled our best estimate 5-year cumulative target probability of default of 6%. 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, or the Portuguese data available to us. 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, and by the fact that RiskCalc\(^\text{TM}\) for Portuguese private companies is a powerful rating tool. However, financial statements fail to fully capture the diversification and management sophistication benefits enjoyed by many of the larger firms.

Thus, whilst RiskCalc\(^\text{TM}\) Portugal predicted lower than average PDs for larger companies, analysis showed that it was not completely capturing the impact of these “externalities”. Following this analysis, we made adjustments to the final calibration for companies to align the predicted PDs with observed default rates. These adjustments are gradually applied to the largest firms, resulting in an approximate 1 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 calibration transforms the score output into easily interpretable probabilities of default, which in turn are mapped to a rating grade scale\(^32\).

Ratios And Their Relation To Default

RiskCalc\(^\text{TM}\) for Portuguese private companies uses seven factors, which fall within the following broad categories: leverage/gearing, profitability, debt coverage, liquidity and activity. 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 (precise definitions of these ratios as well as an explanation of how the ratios relate to Portuguese accounting standards, can be found in the Appendices).

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. RiskCalc\(^\text{TM}\) Portugal contains two measures of the leverage or gearing of a firm: the Equity ratio and the Bank Debt ratio.

---

28 See Appendix D for a fuller description of this.
29 We have based our calibration curve on an exponential function.
30 Again, more details are available in Appendix D.
31 By “less steep” we mean that the relation between the highest predicted PD and the lowest predicted PD is lower.
32 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.
The Equity ratio measures the relation of a company’s equity to its liabilities. 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\textsuperscript{33}.

The Bank Debt ratio quantifies the proportion of a company’s liabilities owed to credit institutions. Debts to credit institutions are significant because they will need to be repaid with cash, unlike for example group debts, and are interest bearing, unlike for example most trade debt. Figure 6 below demonstrates that firms with higher proportions of debts to credit institutions defaulted more frequently than those with low proportions.

---

\textsuperscript{33} The figures of the relationship to default of the factors are based upon the calibration data set.
**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™ Portugal, we reviewed many possible measures of profitability for example Ordinary Profit Over Assets, ROE, 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. Following these analyses we chose Net P&L over Assets, which measures the post-tax profit the firm makes as a proportion of the amount of assets used to generate that profit. Our hypothesis, that firms with lower profitability would subsequently default more frequently, was confirmed by the data as can be seen in Figure 7.

![Figure 7](image)

**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 Portuguese 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 who are failing to generate sufficient cash flow out of their ordinary activities to cover their financial expenses, tend to default more frequently.

The second debt coverage ratio, Cash Flow over Liabilities, measures the extent to which liabilities could be re-paid from the cash generated from ordinary activities before the impact of depreciation and provisions. As can be seen from Figure 8, the data strongly supported our expectation that firms with lower levels of cash flow relative to their liabilities would default more frequently.
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 provisioning adjustments.

**Liquidity**

There are many different liquidity ratios described in financial analysis texts, but at heart they measure the same thing, with people taking different views on how much value one should give to different types of current assets. The RiskCalc™ Portugal model uses the Current Ratio, which measures the proportion of a firm’s short term accounts payable which can be covered by the firm’s current assets. Figure 9 demonstrates that companies that defaulted generally had lower levels of current assets relative to current liabilities than firms which did not default.
Activity
The final ratio included in the RiskCalc™ Portugal model 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.

The Weights
The output of the model is not only determined 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 Portuguese private companies on the whole data sample.
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 Portuguese private companies are accompanied with two additional pieces of information for each ratio: the percentile in which the value for the ratio lies; and the relative contribution for each ratio.

### Empirical Tests

Historically, the primary performance measure used by academics has been the level of misclassification errors for a model, which assumes that there is some score/cut-off below which firms are rejected (and above which they are accepted) and then measures the percentage of misclassifications. This is calculated based on the percentage of defaulting firms that are accepted, and the percentage of non-defaulting firms that are rejected, and depends upon 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.

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, 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 11** shows what the power curves for a typical model, a “perfect” model and a “random” model would look like.

---

### Table 2: RiskCalc For Portuguese Private Companies: Relative Weights of Risk Factor Categories

<table>
<thead>
<tr>
<th>Category</th>
<th>Factors</th>
<th>Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage / Gearing</td>
<td>Equity Ratio, Bank Debt</td>
<td>21%</td>
</tr>
<tr>
<td>Profitability</td>
<td>Net P&amp;L / Assets</td>
<td>17%</td>
</tr>
<tr>
<td>Debt Coverage</td>
<td>Debt Service Coverage, Cash Flow/ Liabilities</td>
<td>34%</td>
</tr>
<tr>
<td>Liquidity</td>
<td>Current ratio</td>
<td>11%</td>
</tr>
<tr>
<td>Activity</td>
<td>Interest Expense/ Turnover</td>
<td>17%</td>
</tr>
</tbody>
</table>

---

34. These percentiles are based on the overall data set, which was used in development of the RiskCalc Portugal model.

35. Of course, whether being in a top percentile is good or bad, 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 Interest Expense ratio is bad (since high levels of Interest Expense are bad).

36. A discussion of the calculation of relative contributions can be found in “RiskCalc™ for Private Companies: Moody’s Default Model”.

37. 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.

38. 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.

39. 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.
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 11 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 other developments, in addition to checking the absolute performance of the rating tool, we compared the performance of our tool to that of Altman’s Z-score\(^\text{40}\), a benchmark chosen for its popularity in accounting and financial analysis texts. As one can see from Figure 12, the tool we developed significantly outperforms the Z-score. Table 3 presents the RiskCalc\(\text{TM}\) Portugal Private firm model’s accuracy ratio in the “validation” sample\(^\text{41}\), using the Z-score as a benchmark.

---

\(\text{40. Z-Score} = 6.56\times[\text{Working Capital/Assets}] + 3.26\times[\text{Retained Earnings/Assets}] + 6.72\times[\text{EBIT/Assets}] + 1.05\times[\text{Net Worth/Liabilities}].\)

\(\text{41. This is the sample where most of the defaulted firms had been used in development, but where none of the non-defaulted firms had been used in development.}\)
There are a few clear messages from Table 3. Firstly, RiskCalc™ Portugal 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 Portuguese firms. Secondly, 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 previous developments, 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, a luxury we didn’t have in Portugal. 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 Portugal 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 5 presents the validation results of the model on sub-samples by industry, size of firm 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™ Portugal Private firm model across industries, and size groups42, this demonstrates the fact that powerful rating tools are better at identifying firms which subsequently default as the point of default approaches.

### Table 3

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>RiskCalc™ Portugal</td>
<td>61.1%</td>
</tr>
<tr>
<td>Z-score</td>
<td>22.2%</td>
</tr>
</tbody>
</table>

### Table 4

<table>
<thead>
<tr>
<th>Defaults</th>
<th>Non-Defaults</th>
<th>Belgium</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>73.3%</td>
<td>67.8%</td>
</tr>
<tr>
<td>Yes</td>
<td>No</td>
<td>73.0%</td>
<td>66.3%</td>
</tr>
<tr>
<td>No</td>
<td>No</td>
<td>72.5%</td>
<td>65.1%</td>
</tr>
</tbody>
</table>

* This 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

<table>
<thead>
<tr>
<th>Split</th>
<th>Sector</th>
<th>Accuracy Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry</td>
<td>Construction</td>
<td>62.6%</td>
</tr>
<tr>
<td>Industry</td>
<td>Manufacturing</td>
<td>72.3%</td>
</tr>
<tr>
<td>Industry</td>
<td>Services</td>
<td>58.1%</td>
</tr>
<tr>
<td>Industry</td>
<td>Trade</td>
<td>61.8%</td>
</tr>
<tr>
<td>Size</td>
<td>Small</td>
<td>62.1%</td>
</tr>
<tr>
<td>Size</td>
<td>Medium</td>
<td>68.9%</td>
</tr>
<tr>
<td>Size</td>
<td>Large</td>
<td>76.7%</td>
</tr>
<tr>
<td>Date</td>
<td>1 year before default</td>
<td>74.2%</td>
</tr>
<tr>
<td>Date</td>
<td>2 years before default</td>
<td>65.2%</td>
</tr>
<tr>
<td>Date</td>
<td>3 years before default</td>
<td>58.5%</td>
</tr>
</tbody>
</table>

42 Here we have defined “Small” as those firms with turnover of less than €2.5m, “Medium” as those with turnover of between €2.5m and €10m and “Large” as all other firms.
Implementation Tips

There are a few points, which one should bear in mind when using RiskCalc™ for Portuguese 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™ Portugal produces very powerful results. However, prudence dictates that if you have access to additional important information you should consider it. For example, if you are 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.43

A counterintuitive result of the model is that its PDs often appear “too low”, and therefore that the credit quality appears “too high”. Many users are used to higher default rate projections for individual companies. The average probability of default for middle market firms of 1.5% per year seems to make perfect sense until one actually sees the individual credits to which this is applied, and one considers that this is consistent with Ba2 probability of default (most people consider private credit to be in the B2-B1 range on average, not the Ba2 range). While we have used a 1.5% figure, the user should recognise that we want the model to be unbiased. That is, it represents our best statistical estimate of the future probability of default. In contrast, a natural inclination of an underwriter is to be pessimistic, as the cost to being too optimistic, and extending a loan to a firm which subsequently defaults, is generally higher than the lost revenue from rejecting a customer.

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 annualised44 (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 re-structuring 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 Portuguese 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.45

43. 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.
44. 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.
45. For example, as a result of the careful regulation of financial institutions, the default rates for these firms are generally very low.
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 Portuguese model, careful attention has been paid to how financial ratios could differ between Portugal and other western countries considering the particularities of the Portuguese 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 Portuguese 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.
Appendix A: Factors And Inputs For RiskCalc™ Portugal

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 which 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 6, shows the accounting inputs required, as well as the location in a financial statement where they would be located.

Table 6: RiskCalc™ For Portuguese Private Companies: Model Inputs

<table>
<thead>
<tr>
<th>Area Of Financial Statement</th>
<th>Line Items, English</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balance Sheet, Assets</td>
<td>Current Assets</td>
</tr>
<tr>
<td>Balance Sheet, Liabilities</td>
<td>Equity</td>
</tr>
<tr>
<td></td>
<td>Accounts payable (due within 1 year)</td>
</tr>
<tr>
<td></td>
<td>Accounts payable (due after more than 1 year)</td>
</tr>
<tr>
<td></td>
<td>Debt to credit institutions (due within 1 year)</td>
</tr>
<tr>
<td></td>
<td>Debt to credit institutions (due after more than 1 year)</td>
</tr>
<tr>
<td></td>
<td>Total Liabilities</td>
</tr>
<tr>
<td>Profit And Loss</td>
<td>Sales of merchandise and goods</td>
</tr>
<tr>
<td></td>
<td>Services rendered</td>
</tr>
<tr>
<td></td>
<td>Depreciation of tangible and intangible fixed assets</td>
</tr>
<tr>
<td></td>
<td>Provisions</td>
</tr>
<tr>
<td></td>
<td>Interest and similar expenses</td>
</tr>
<tr>
<td></td>
<td>Extraordinary Income</td>
</tr>
<tr>
<td></td>
<td>Extraordinary Expense</td>
</tr>
<tr>
<td></td>
<td>Corporate tax for the year</td>
</tr>
<tr>
<td></td>
<td>Net P&amp;L</td>
</tr>
</tbody>
</table>

Table 7 shows how these line items are combined to create the accounting concepts used within RiskCalc™ Portugal (we have only included an item in this table if it is not a clearly defined input).

Table 7: RiskCalc™ For Portuguese Private Companies: Inputs And Accounting Concepts

<table>
<thead>
<tr>
<th>Concept</th>
<th>Calculation From inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Assets</td>
<td>Equity + Total Liabilities</td>
</tr>
<tr>
<td>Total Accounts Payable</td>
<td>Accounts payable (due within 1 year)+</td>
</tr>
<tr>
<td></td>
<td>Accounts payable (due after more than 1 year)</td>
</tr>
<tr>
<td>Bank Debt</td>
<td>Debt to credit institutions (due within 1 year) +</td>
</tr>
<tr>
<td></td>
<td>Debt to credit institutions (due after more than 1 year)</td>
</tr>
<tr>
<td>Turnover</td>
<td>Sales of merchandise and goods +</td>
</tr>
<tr>
<td></td>
<td>Services rendered</td>
</tr>
<tr>
<td>Ordinary P&amp;L</td>
<td>Net P&amp;L +</td>
</tr>
<tr>
<td></td>
<td>Corporate Tax for the year –</td>
</tr>
<tr>
<td></td>
<td>Extraordinary income +</td>
</tr>
<tr>
<td></td>
<td>Extraordinary Expense</td>
</tr>
</tbody>
</table>

Table 8 shows the calculation of the ratios in RiskCalc Portugal.

Table 8: RiskCalc™ For Portuguese Private Companies: Ratio Calculations

<table>
<thead>
<tr>
<th>Category</th>
<th>Ratio Name</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage</td>
<td>Equity Ratio</td>
<td>Equity / Total Accounts Payable</td>
</tr>
<tr>
<td></td>
<td>Bank Debt Ratio</td>
<td>Bank Debt / Total Liabilities</td>
</tr>
<tr>
<td>Profitability</td>
<td>Net P&amp;L / Assets</td>
<td>Net P&amp;L / Total Assets</td>
</tr>
<tr>
<td>Debt Coverage</td>
<td>Debt Service Coverage</td>
<td>(Ordinary P&amp;L+ Depreciation)/ Interest and similar Expenses</td>
</tr>
<tr>
<td></td>
<td>Cash Flow / Liabilities</td>
<td>(Ordinary P&amp;L + Depreciation + Provisions) / Total Liabilities</td>
</tr>
<tr>
<td>Liquidity</td>
<td>Current Ratio</td>
<td>Current Assets / Accounts Payable (due within 1 year)</td>
</tr>
<tr>
<td>Activity</td>
<td>Interest expense / Sales</td>
<td>Interest and similar Expenses / Turnover</td>
</tr>
</tbody>
</table>
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:

\[
Y = \frac{e^{\alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \ldots + \alpha_n X_n}}{1 + e^{\alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \ldots + \alpha_n X_n}}
\]

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 13 for the case of a model with one independent variable, 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, \(\alpha_j\) to minimise the error between the observed and predicted values of \(y\) (i.e. the \(\delta_i\) in Figure 13). This is done by minimising the loss function, which in this case is the sum of all \(\ln(Y_{\text{predicted}})\) for defaulted customers minus the sum of all \(\ln(1-Y_{\text{predicted}})\) for healthy customers, i.e.

\[
\text{Loss} = \sum ((Y_{\text{observed}}) \ln(Y_{\text{predicted}}) - (1 - Y_{\text{observed}}) \ln(1 - Y_{\text{predicted}}))
\]
Appendix C: Testing Metrics

Power Curves
A power curve\(^{46}\) is constructed by plotting, for each score, \(m\), the proportion of defaults with a score worse than \(^{47}\) \(m\), 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\(^{48}\).
- 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:

\[
power(b) = \frac{\sum_{i=1}^{b} D(i)}{\sum_{i=1}^{B} D(i)},
\]

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 14 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 14](image)

**Figure 14** 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:

\[
p(m) = \bar{p} \times \frac{\partial power(m)}{\partial m},
\]

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 \(m\).

---

46. Also known as the CAP plot.
47. Here “worse than” is taken to indicate that the firm is higher risk, i.e. more likely to default.
48. 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 which 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 11 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 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, which is the point of default used during development of the RiskCalc™ Portugal model. Thus we excluded all statements whose closing date was within 12 months of the reported default 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 12 and 35 months prior to the insolvency date and calculated its score. Where no statement was available in this 12 to 35 month period, we excluded the observation. For example, if a firm had defaulted on October 1st 1998, we would have excluded any statements, which closed 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”49, and a default rate was calculated for each bin50.

This is the observed calibration “curve” (the bars in Figure 15), which is then smoothed to overcome data anomalies and relate a score to a default rate (the curve in Figure 15). The “height”, or intersect with the y-axis, of this curve is then adjusted to ensure that the predicted default rate across our whole portfolio reflects the aggregate probability of default assumption.

\[ \text{Score / bin} \]

\[ \text{Default rate} \]

The five-year calibration curve was constructed using the curves of a five year cohort starting in 1995. This approach consists of rating all firms within a year, for example 1993, and then following their performance during the next 5 years. A score within a given cohort was flagged as defaulting if it defaulted at some point between 6 and 65 months after the date of the financial statement. We excluded statements for companies that defaulted within the first 6 months following the date of the financial statement date. This 6 month “lag” was included to take into account the lag between the publication and the date of the financial statement.

Having identified those firms which defaulted within 5 years of being rated, we created score “bins” for each cohort, and calculated the average default rate for each bin51. This produced our calibration curve, which we then smoothed and adjusted to our best estimate of the aggregate 5-year cumulative probability of default.

49. 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).

50. 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.

51. This is defined as the number of defaults in the bucket in the 5 year period divided by the number of firms in the bucket at the start of the period.
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.

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](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 short-hand 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, 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.

---

52. 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.