Overview

In recognition of the growing need for benchmarks in the rating of middle market companies, Moody’s KMV is creating models for estimating firm probabilities of default using financial statement data. RiskCalc for Nordic private companies has been designed and calibrated for use on private companies in Denmark, Finland, Norway and Sweden. It is the latest in a suite of European models that are being co-developed with Mercer Oliver Wyman, 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 the Nordic region joins RiskCalc™ private firm models for the US, Canada, Australia, Germany, Spain, France, the UK, Belgium, the Netherlands, Mexico, Japan, Portugal, Italy, Austria, Singapore and a model for US Banks allowing one consistently to attach probabilities of default to firms throughout the world1. As a powerful, objective model, it serves the interests of institutions, borrowers and investors alike.

This report documents the following:

• A description of the database of financial statements used in developing Moody’s RiskCalc™ for Nordic private companies
• A description of the methodology used to develop the model and calibrate it to the default experiences in each of the countries covered by the model,
• A comparison of the relationships of the selected financial ratios to default, and
• Empirical tests of the model, demonstrating its strong performance both across the Nordic region and in each of the four countries.

The following is a self-contained description of the development and validation of Moody’s RiskCalc™ model for Nordic 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”.

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1. For the most up to date list of available models, the reader is referred to the Moody’s KMV website www.moodyskmv.com
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:** whilst 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 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. **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, whilst 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. Whilst we are confident that the model we have developed for the Nordic region 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 Nordic private companies\(^3\) has been developed in co-operation with Mercer Oliver Wyman, 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.

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2. Of course, the level of validation that can be performed depends on the amount of data that 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.

3. By “private companies” we refer to those firms who do not have publicly quoted and traded equity.
An Introduction To The Modelling Approach And The Nordic Model

There are three steps to the core RiskCalc™ modelling process: transformation, modelling, and mapping. In the transformation stage variables are converted from sometimes noisy raw data into more useful and powerful representations that aid in default prediction. In the second step, these transformed variables are combined statistically to yield a risk score. In the third step, the score is mapped to an empirical default probability. Prior to these steps, significant analysis takes place to select a subset of variables that predict default well, and after the model is built significant work is done to validate the model and give confidence that it is robust and will perform well in the future. Further details of our methodology can be found in the Modelling Framework section.

In developing the RiskCalc model for Nordic private companies, an additional step was included during which models and factors were selected and optimised on individual countries and their performance on a test sample was examined and compared with the performance of a Nordic model. Following this analysis, it was felt that the greater robustness afforded by the use of a larger pan-Nordic data set merited development and calibration of a Nordic model. The factors and “weights” were chosen so as to be consistent across the region, and then the model was individually calibrated to each country.

Model Factors And Structure

RiskCalc™ for Nordic private companies uses seven factors which fall within the following broad categories: leverage/gearing, profitability, debt coverage, liquidity and current asset structure. 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\footnote{Precise definitions of these ratios, as well as an explanation of how the ratios relate to Danish, Finnish, Norwegian and Swedish accounting standards, can be found in Appendix A.}

**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™ Nordic model the leverage or gearing of a firm is captured by two measures: the Liabilities ratio and the Net Indebtedness ratio.

The Liabilities ratio measures the level of a company's total liabilities relative to its assets\footnote{In this ratio, total liabilities includes both the subordinated debt for a firm and its compulsory provisions for things such as future tax liabilities and pensions obligations.}. The ratio is an important indicator of a company’s financial stability since firms with high levels of liabilities may well prove less able to survive a downturn, or a period when the company is making losses. This effect is magnified by the existence of regulations in the Nordic region such as a Finnish law requiring directors of public limited companies to call a meeting with a view to liquidating a firm if too much of the firm’s paid-in share capital is eroded\footnote{Given such laws, it is unsurprising that measures of liabilities or equity should be highly indicative of official default. It is our view that this legal tying together of leverage and corporate insolvency, together with the fact that we only had access to official default events, would potentially mask the power of other variables for predicting other types of default. Since it is the aim of RiskCalc to help in assessing the risk of experiencing a credit loss on an obligation, not just the risk of an official default, we have taken this into account when interpreting the statistical results and specifying the final model.}. Our initial assumption, that on average companies which subsequently defaulted had a higher level of this ratio than those which did not, was confirmed by the data, as can be seen in Figure 1\footnote{The figures of the relationship to default of the factors are based upon the Nordic calibration data set. A description of the charts on the right can be found in the Modelling Framework section – essentially they indicate the relative level of defaults associated with the percentile of a ratio value. The charts on the left show the distribution of ratio values for defaulting and non-defaulting firms.}.

![Figure 1](https://example.com/image1.png)

**Firms With Higher Liabilities As A Proportion Of Total Assets Default More Frequently**

- **0%** Solvent
- **20%** Insolvent

\[\text{Percentile} \quad \text{Default Rate}\]

\[0\% \quad 20\% \quad 40\% \quad 60\% \quad 80\% \quad 100\%\]
The Net Indebtedness ratio quantifies the level of a company's short-term debts, net of the firm's cash, relative to its total assets. This is a measure of a firm's short-term gearing, and hence a firm's ability to withstand temporary downturns or losses. **Figure 2** below demonstrates that firms with high levels of short-term debts outstanding defaulted more frequently than those with low levels of 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™ for Nordic private companies, 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. Following these analyses we chose Pre-tax P&L over Assets, which measures the recurring profit the firm makes before the impact of tax. Our hypothesis, that firms with lower profitability would subsequently default more frequently, was confirmed by the data as can be seen in **Figure 3**.

**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 Nordic private companies.

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8. This doesn’t include short-term provisions or subordinated loan capital.
The Debt Service Coverage ratio measures the level of Ordinary profit relative to a company’s financial expenses. This debt service coverage ratio shows the relation between a company’s profit from ordinary activities and its financial payments. As can be seen from Figure 4, those firms that are failing to generate sufficient profit from their ordinary activities to cover their financial expenses tend to default more frequently.

The second debt coverage ratio, EBITDA over Short-term Debts, measures the extent to which short-term debts could be re-paid from pre-tax Cash Flow. As can be seen from Figure 5, the data strongly supported our expectation that firms with lower levels of cash flow relative to their short-term debts 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: 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.

**Liquidity**

There are many different liquidity ratios described in financial analysis texts: at heart they measure the same thing, despite differing views on how much value one should give to different types of current assets. The RiskCalc™ Nordic model uses a modified version of the current ratio, with Total Assets replaced by Total Liabilities in the denominator. Figure 6 demonstrates that companies that defaulted generally had lower levels of the modified current ratio than firms that did not default.

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9. Ordinary P&L is the pre-tax profit before the impact of extraordinary items, or alternatively, the profit from operating activities plus the difference between financial income and financial expenses.

10. Thus the ratio is calculated as (Current Assets – Short-term Debt) / Total Liabilities.
Other

Whilst Current Assets structure, the final ratio that we have included in the RiskCalc rating tool, 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\(^\text{11}\). 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 a value closer to their market value, than is the case for lower quality/less liquid current assets such as inventories. Figure 7 demonstrates that, as expected, firms with better quality current assets, i.e. higher levels of cash, defaulted less frequently.

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 1 shows the relative contributions of the factors in RiskCalc™ for Nordic private companies.

<table>
<thead>
<tr>
<th>Category</th>
<th>Factors</th>
<th>Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage / Gearing</td>
<td>Liabilities, Net Indebtedness</td>
<td>34%</td>
</tr>
<tr>
<td>Profitability</td>
<td>Pre-tax P&amp;L / Assets</td>
<td>20%</td>
</tr>
<tr>
<td>Debt Coverage</td>
<td>Debt Service Coverage</td>
<td>25%</td>
</tr>
<tr>
<td>Liquidity</td>
<td>EBITDA/ Short-term Debts</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>Modified Current Ratio</td>
<td>6%</td>
</tr>
<tr>
<td>Other</td>
<td>Current Asset Structure</td>
<td>15%</td>
</tr>
</tbody>
</table>

\(^{11}\) 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.
Modelling Framework

RiskCalc™ for Nordic 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 Mercer Oliver Wyman. 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. Our modelling approach can be briefly summarised in the following three steps:

- **Univariate Analysis and Transformation**: the aim of univariate 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.

An important additional step in the process of developing the RiskCalc model for Nordic private companies was to compare the performance of models developed specifically for each of the Nordic countries, with the performance of a model developed on a Pan-Nordic data set. Following this analysis, it was felt that the greater robustness afforded by the use of a larger pan-Nordic data set merited development and calibration of a Nordic model. Thus a single set of factors and their “weights” were selected. This single model was then individually calibrated to each country reflecting the different anchor points of the models and the different predictive power of the financial statement based ratios.

**Univariate Analysis And Transformation**

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 creditworthiness. 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.

- **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.

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12. These percentiles are based on the data set for each country, which was used in calibration of the RiskCalc Nordic model. Thus for a given value of, for example, Liabilities / Assets, the percentile returned would depend on the country in which the firm was based.

13. 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 Liabilities / Assets ratio value is good (as high profitability levels are good), but being in the top 5% for the Liabilities ratio is bad (since high levels of liabilities are bad).

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

15. 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).

16. More details on the anchor point PD figures used can be found in the section on Aggregates Probability of Default Assumptions below. Performance results can be found in the section on Empirical Tests.

17. 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.
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 Liabilities / Assets, where we would expect higher values to be associated with higher default rates. If the data indicated that higher values were associated with lower levels of default, then we would not include Liabilities / 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 and 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 8, 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. (ST Debt – Cash) / Assets on the left panel), or always negative, so that a lower ratio value indicates a higher probability of default (e.g. EBITDA / Short-term debt on the right panel). It is also apparent from Figure 8 that this relationship is generally not a straight-line relationship (i.e. it is “non-linear”).

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 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 that 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.

18. 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.
19. 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.
20. One of the most widely documented classes of non-monotonic ratios is that of growth ratios, which often exhibit a U shaped relation with default.
21. 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.
22. Thus, for example we estimated weights for a model including only EBITDA over Short-term Debts, and for a model with only Ordinary P&L 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.
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\(^{23}\). When deciding on the final factors and weights to use, we combined an analysis of the power of the different models, as measured by the accuracy ratio, with our experience and practical considerations. 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 model should not be too dependent on any one factor or type of factor,
- the factors and their weights should be intuitive,
- the model should have high explanatory power.

**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 in the section on Aggregate Probability of Default Assumptions later in the document, 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 described 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\(^{24}\). In order to avoid anomalies caused by the data, the calibration curve is smoothed whilst ensuring that the tails retain their exponential nature\(^{25}\). This calibration curve is then adjusted so that the implied population default rate matches our best estimate of the anchor point default rate.

As mentioned above, the model has been separately calibrated in each country, reflecting both different views on anchor point PDs and the different predictive power of financial statement based ratios. On the latter point, it became apparent during the univariate analysis that for the Swedish data, it was generally harder to identify from financial statement information those firms that would subsequently default. For example, if one looks at Figure 9 which shows the relation between Liabilities / Assets and default in Finland and Sweden, it is clear that in Finland this ratio more clearly differentiates between defaulting and non-defaulting firms\(^{26}\).

\[\text{Figure 9}
\]

Financial Statement Based Variables Discriminate Better In Finland Than Sweden

![Financial Statement Based Variables Discriminate Better In Finland Than Sweden](image)

This means that if, for example, 10,000 Finnish and 10,000 Swedish firms each containing the same number of defaults, were ranked using this ratio, the best (worst) 1,000 Finnish firms would contain fewer (more) defaults than the best (worst) 1,000 Swedish firms\(^{27}\). If we calibrated the Swedish “model” using the default rate curve for the Finnish firms, then we would over-predict the default rate for the worst firms, and under-predict the default rate for the best firms, leading to poor/costly pricing and capitalisation decisions.

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\(^{23}\)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.

\(^{24}\)See Appendix D for a fuller description of this.

\(^{25}\)We have based our calibration curve on an exponential function.

\(^{26}\)This figure shows the relative default rates, thus allowing us to abstract from the actual level of defaults in the data set.

\(^{27}\)If we then calibrated the Liabilities / Assets ratio, then this “model” should predict lower (higher) default rates for the best (worst) 1,000 Finnish firms than the best (worst) 1,000 Swedish firms.
The process for calibrating the RiskCalc Nordic model to a 5-year horizon is conceptually similar to the 1-year calibration, except that the un-smoothed calibration curve is derived using a cohort approach. This curve was then smoothed and its “height” adjusted to ensure that the average predicted default rate equals our best estimate of the 5-year cumulative target probability of default. 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, insofar as their ratios generally indicate better credit quality. However, financial statements often fail to capture fully 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™ for Nordic private companies predicted higher PDs for smaller firms and lower than average PDs for larger companies, it was not completely capturing the impact of these “externalities” in all countries. We therefore made adjustments to the calibrations for companies to align the predicted PDs with observed default rates.

In the same way that there are differences in default rates between firms of different sizes, so there are differences in default rates across industries. Our experience in developing rating tools, and hence our expectation in developing RiskCalc™ for private companies, is that whilst some of these industry differences are reflected in financial statement based ratios, the full extent of these differences is not. We therefore decided to examine the performance of the RiskCalc™ Nordic model and the average PDs predicted within different sectors and compare them with our calibration data. Whilst the tool proved to be very powerful both across and within industries, there were some differences between predicted and observed default rates across industries in some countries. Given the power of the tool we felt it was best to deal with observed industry specific differences as part of the calibration, rather than, for example, through the use of industry indices which would increase the data burden on end users.

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 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 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 information that each ratio carries about the likelihood of default.

**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. 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.

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

Figure 10

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 10 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 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 with 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. A more practical approach, which we consider ensures that the results for a model are stable, is to use a large holdout sample that has not been used at any point in the development of the model.

Given the richness of the combined dataset, we were able to construct a large holdout sample on which to test the performance of our final tool37. This sample contained over 500,000 financial statements from more than 95,000 firms, including about 3,300 firms which defaulted. As in the 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-score38, a benchmark chosen for its popularity in accounting and financial analysis texts. As one can see from Figure 11, the tool we developed significantly outperforms this model39.

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37. We didn’t have sufficient numbers of defaults in Finland for this approach, and re-used the development sample defaults, but non-development non-defaults. The vast majority of statements in the Nordic validation sample were never used during development of the rating tool.

38. We have not used Altman’s Z-score due to poor availability of retained earnings and intangible assets. We therefore used the following “model” as a proxy for the Z-score, \( Z^* = 6.56 \times \text{Working Capital/Assets} + 3.26 \times \text{Equity/Assets} + 6.72 \times \text{EBIT/Assets} + 1.05 \times \text{Equity/Liabilities} \). We would expect this to have a similar Accuracy Ratio to the actual Z-score.

39. This power curve and all of the following accuracy ratios (except time to default based figures) are based on the Nordic validation sample which consists of the most recently available financial statement for defaulted firms and all statements for non-defaulted firms.
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 2 presents the RiskCalc™ Nordic Private firm model's accuracy ratio in the validation sample, using the modified version of the Z-score as a benchmark.

Table 2
RiskCalc™ For Nordic Private Companies: Accuracy Ratios

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>RiskCalc™ Nordic</td>
<td>68.1%</td>
</tr>
<tr>
<td>Z-score</td>
<td>53.8%</td>
</tr>
</tbody>
</table>

There are a few clear messages from Table 2. First, the RiskCalc™ Nordic 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 firms in the Nordic region. Second, and this is a general characteristic for the RiskCalc™ suite of models, RiskCalc™ is a significant improvement on the Z-Score benchmark.

Table 3 presents the validation results of the model on sub-samples by industry, size and the date of the financial statements relative to default for the Nordic validation sample. As shown, the model is satisfactorily stable across the different classifications. Apart from demonstrating the stability of the RiskCalc™ Nordic Private firm model across industries and size groups, this demonstrates the fact that this powerful rating tool is better at identifying firms which subsequently default as the point of default approaches, and that it dominates the modified Z-score along these dimensions.

40. Performance of the model by size and industry in each of the individual countries can be found in Appendix C.

41. Here we have defined “Small” as those with assets of less than ~€0.5m, “Medium” as those with assets of between €0.5m and €2.5m and “Large” as all other firms.
Table 4 presents the validation results of the model in each of the individual countries. Apart from the clear dominance of the modified Z-score by the RiskCalc Nordic model, there is a clear difference in performance of the model across countries. However, a similar pattern of performance across countries can be seen for the modified Z-score indicating that this difference does not reflect a weakness in the selected model, but rather the lower predictiveness of financial statement based variables in Sweden.

The Dataset

The purpose 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 Nordic private companies is to provide a probability of default (PD) for private Nordic companies with total assets of more than €250,000. 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 assets of more than €250,000.
- **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 in 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. 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.

42. Similar results were seen during development on an individual ratio basis.
43. 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.
44. 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.
Descriptive Statistics Of The Data

Table 5 provides a summary of the data sets used in development, validation and calibration of RiskCalc™ for Nordic private companies and compares it with those used in developing other RiskCalc™ models. By combining data sets from Denmark, Finland, Norway and Sweden we have had access to a very large database of financial statement and credit event information, allowing us to develop a powerful, robust model.

<table>
<thead>
<tr>
<th>Information On Private Firm Sample Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Span</td>
</tr>
<tr>
<td>--------------------------</td>
</tr>
<tr>
<td>Nordic Region</td>
</tr>
<tr>
<td>UK</td>
</tr>
<tr>
<td>France</td>
</tr>
<tr>
<td>Spain</td>
</tr>
<tr>
<td>North America</td>
</tr>
</tbody>
</table>

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 12. This illustrates the difference in coverage between the RiskCalc™ Nordic data set and the data sets available in other countries, as well as providing the time coverage of individual Nordic countries. The shorter time period covered by the Danish and Finnish data sets relative to Sweden, reflects the impact of data privacy laws/agreements in the former.

Given the longer time period covered by the Swedish data, together with the fact that in GDP terms it is the largest Nordic country, it is unsurprising that the overall data set is dominated by Swedish firms as illustrated in Figure 13a. However, in development we compensated for this by “biasing” the selection of defaulted firms towards the smaller countries, as can be seen in Figure 13b, in order to ensure that the model would be predictive in all Nordic countries.
As in other RiskCalc Private firm developments, the majority of statements available for use in developing, validating and calibrating the rating tool European countries were from smaller firms. The size distribution of the statements used in developing and calibrating RiskCalc™ for Nordic private companies is illustrated in Figure 14, using Total Assets as the size measure due to a lack of Turnover information for the smallest firms in Denmark. Combining the data for the four countries has allowed us to ensure that the data set on which the model was developed included more large firms, which in turn helped to ensure powerful performance on such firms.

Given the predominance of smaller firms in the data set, it is unsurprising that Figure 15 shows that the sample is dominated by trade and service firms.

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45. In order to facilitate “comparisons” in this documentation, we have used a fixed conversion rate between local currencies and the Euro for Denmark, Norway and Sweden. During actual development work, local currencies were used, although for the majority of ratios the currency is largely irrelevant due to the fact that both numerator and denominator are in the same currency.

46. 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 Nordic 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 proposed definitions would be inappropriate in certain markets. Thus, for example, whilst a “90 days past due” definition of default might be considered a reasonable indicator that credit losses will be incurred in Spain and several other European countries, in Italy it is often only when a firm is approximately 180 days past due that there is a real expectation that a creditor may experience losses.

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. 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 influence the choice of 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 Nordic private companies differs from the development of RiskCalc™ US in that, in developing the first version of the model for Nordic private companies, we have used publicly available data and have relied on corporate insolvency events to identify the key indicators of credit losses. The insolvency events used in each country were:

- Denmark - bankruptcy in progress or completed
- Finland - bankruptcy filing by debtor or an adjudication of bankruptcy.
- Norway - liquidation
- Sweden - bankruptcy petition or declaration of bankruptcy.

The definition of default targeted when calibrating the RiskCalc™ for Nordic private companies model 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.

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47. We believe that those private firm score-cards that 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.

48. Our experience is that many factors that 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.

49. There were a number of other definitions available in the different data sets, however it was felt that it would be best to exclude them from the definition of default used in developing the model: either they were very infrequent compared to the selected defaults (e.g. court administered compositions in Norway); or they were considered as “weak” definitions because firms continued to function for several years thereafter (e.g. injunctions to pay in Sweden).

50. Creditor filings often appeared spurious as they did not necessarily result in the debtor being adjudicated bankrupt.

51. More details on the calibration of the model are contained within the Modelling Framework section above, and in Appendix D. Briefly, the calibration step maps the output of an algorithm to a probability of default.
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.

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 Nordic 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 (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 that captures more cyclicity should be calibrated to a figure closer to the observed figure, whilst a tool which captures less cyclicity should be calibrated to a figure closer to the long run average default rate.

In deriving an estimate of the anchor point PD for the RiskCalc Nordic model in each country we drew on bank provisioning data and insolvency/reorganisation information. In moving from national insolvency figures to an anchor point, care was taken since these figures are in part driven by size, industry and legal forms not covered by RiskCalc™ for Nordic private companies, and because creditors often incur losses without the debtor entering insolvency or being officially reorganised.

In addition to detailed insolvency data, we analysed Nordic 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:

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

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

In Finland, Norway and Sweden careful consideration was given to the impact of the severe banking crises which they experienced in the late 1980's/early 1990's when governments were forced to step in, nationalising banks, injecting capital or hiving-off bad debts into special asset management companies. The severity of the crisis can be seen in Figure 16, which shows the bankruptcy rate in Finland between 1988 and 2001 divided by the average bankruptcy rate in that period, and similar information for the UK. It shows that whilst recent experience has been similar in the two countries, at the peak of the crisis, the increase in the bankruptcy rate in Finland was much more extreme than in the UK. Much has been written on the causes of the Nordic banking crises, suggesting that such severe losses are unlikely to happen again. Thus, in estimating future default rates, we have not only looked at the historical data, but also considered the likely default experience in a more “normal”/less severe recession.

Figure 16

The Finnish Recession Between 1990 And 1993 Was Unusually Severe
Comparison Of UK And Finnish Default Experiences

52. This assumes that there has not been a structural shift in default rates, e.g. in the US, post the oil shocks.
Based on these analyses, as well as considerations concerning the cyclical nature of the rating tool and the underlying data set used in calibrating the RiskCalc Nordic model, we have used anchor points for the 1 year PD of 1.7%, 1.9%, 2.1% and 2.2% for Denmark, Finland, Norway and Sweden respectively.

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 deriving the North American private model, Moody’s KMV spent considerable effort in examining the relationship between the 1 and cumulative 5 year PDs 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, approximately 4 times the level of the 1-year default rate. Thus in calibrating RiskCalc™ for Nordic private companies for the 5 year horizon in each country, we have used anchor points of 6.8%, 7.6%, 8.4% and 8.8% for Denmark, Finland, Norway and Sweden respectively.

Implementation Tips

There are a few points which one should bear in mind when using RiskCalc™ for Nordic private companies. As with other RiskCalc™ models, we have not included every element that we believe influences 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™ for Nordic private companies 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.

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 (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 Nordic Private Companies

It is also important to bear in mind that, whilst 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.

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53. For more details on this work, we refer the reader to the description in “RiskCalc™ For Private Companies: Moody’s Default Model”.

54. 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.

55. 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.

56. 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.
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 assets of less than €250,000; 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\textsuperscript{57}.

**Conclusions**

The RiskCalc\textsuperscript{™} 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. Careful attention has been paid to how financial 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\textsuperscript{™} for Nordic private companies model should help improve profitability through the credit cycle, be it through use in decisioning, pricing, monitoring or securitisation. Whilst 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.

\textsuperscript{57}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 The RiskCalc™ Nordic Model

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 that a user could reasonably be expected to obtain. Table 6 shows the accounting inputs required in each of the four countries.

Table 6
RiskCalc™ For Nordic Private Companies: Model Inputs

<table>
<thead>
<tr>
<th></th>
<th>Denmark</th>
<th>Finland</th>
<th>Norway</th>
<th>Sweden</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balance Sheet, Assets</td>
<td>Cash At Bank And In Hand</td>
<td>Cash At Bank And In Hand</td>
<td>Cash At Bank And In Hand</td>
<td>Cash At Bank And In Hand</td>
</tr>
<tr>
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<td>Current Assets</td>
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<td>Current Assets</td>
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</tr>
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<td></td>
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<td>Total Assets</td>
<td>Total Assets</td>
<td>Total Assets</td>
<td>Total Assets</td>
<td>Total Assets</td>
</tr>
<tr>
<td>Balance Sheet, Liabilities</td>
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<td>Subordinated Loan Capital</td>
<td>Subordinated Loan Capital</td>
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</tr>
<tr>
<td></td>
<td>Short-Term Debts</td>
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<td>Long-Term Debts</td>
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<tr>
<td>Profit And Loss</td>
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<td>Depreciation &amp; reductions in values</td>
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<td>Depreciation</td>
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<td></td>
<td>Operating P&amp;L</td>
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<td>Operating P&amp;L</td>
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</tr>
<tr>
<td></td>
<td>Result before Extraordinary Items</td>
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</tr>
<tr>
<td></td>
<td>Pre-tax P&amp;L</td>
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</tr>
<tr>
<td></td>
<td>Profit or Loss for the Financial Year</td>
<td>Profit or Loss for the Financial Year</td>
<td>Profit or Loss for the Financial Year</td>
<td>Profit or Loss for the Financial Year</td>
</tr>
</tbody>
</table>

Table 7 shows how these line items are combined to create the accounting concepts used within RiskCalc™ for Nordic private companies (we have only included items in this table that are not clearly defined inputs).

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

<table>
<thead>
<tr>
<th></th>
<th>Denmark</th>
<th>Finland</th>
<th>Norway</th>
<th>Sweden</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Assets</td>
<td>Total Assets</td>
<td>Total Assets</td>
<td>Current Assets + Fixed Assets</td>
<td>Total Assets</td>
</tr>
<tr>
<td>Depreciation</td>
<td>Depreciation</td>
<td>Depreciation &amp; reductions in values</td>
<td>Depreciation + Write-downs</td>
<td>Depreciation</td>
</tr>
<tr>
<td>Pre-tax P&amp;L</td>
<td>Pre-tax P&amp;L</td>
<td>Profit or Loss for the Financial Year + Taxes</td>
<td>Pre-tax P&amp;L</td>
<td>Pre-tax P&amp;L</td>
</tr>
</tbody>
</table>

58 Differences between the inputs reflect the fact that certain items are reported in different parts of the balance sheet or P&L. Thus, for example, Subordinated Loan Capital is reported under Equity in Finland, at the same level as Equity and Debts in Denmark and as part of Debts in Norway and Sweden.
Table 8 shows how these line items are combined to create the ratios used in the RiskCalc™ Nordic model.

<table>
<thead>
<tr>
<th>Category</th>
<th>Name</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage/ Gearing</td>
<td>Liabilities</td>
<td>Total Liabilities / Total Assets</td>
</tr>
<tr>
<td></td>
<td>Net Indebtedness</td>
<td>(Short-term Debts - Cash at bank and in hand) / Total Assets</td>
</tr>
<tr>
<td>Profitability</td>
<td>Pre-Tax P&amp;L / Assets</td>
<td>Pre-Tax P&amp;L / Total Assets</td>
</tr>
<tr>
<td>Debt Coverage</td>
<td>Debt Service Coverage</td>
<td>Ordinary P&amp;L / Financial Expenses</td>
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<td>EBITDA / Short-term Debts</td>
<td>EBITDA / Short-Term Debts</td>
</tr>
<tr>
<td>Liquidity</td>
<td>Modified Current Ratio</td>
<td>(Current Assets - Short-term Debt) / Liabilities</td>
</tr>
<tr>
<td>Other</td>
<td>Current Assets Structure</td>
<td>Cash at bank and in hand / Current Assets</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:

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

(A.1)

where \( Y \) is the dependent variable (i.e. the default/non-default flag) and \( X \) 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 take any value between 0 and 1. This model, as shown in Figure 17 for the case of a model with one independent variable, is S-shaped.

\[ \text{Loss} = \sum (-(Y_{\text{observed}}) \ln(Y_{\text{predicted}}) - (1 - Y_{\text{observed}}) \ln(1 - Y_{\text{predicted}})) \]  

(A.2)

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 \( \alpha_i \) to minimise the error between the observed and predicted values of \( Y \) (i.e. the \( \delta_i \) in Figure 17). This is done by minimising the loss function, which in this case is minus 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.
Appendix C: Testing Metrics And Individual Country Results

**Power Curves**

A power curve\(^{59}\) is constructed by plotting, for each score, \(m\), the proportion of defaults with a score worse than\(^{60}\) \(m\), 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\(^{61}\).
- 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:

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

where, \(\text{power}(b)\) is the height of the power curve in bin \(b\) and \(D(i)\) is the number of defaults in bin \(b\).

The result is **Figure 18** below which plots the power curve for a metric \(M\) (the line \(\text{power}(M)\), 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.

---

59. Also known as a CAP plot.
60. Here “worse than” is taken to indicate that the firm is higher risk, i.e. more likely to default.
61. 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.
Figure 18 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:

\[
p(m) = \bar{p} \times \left[ \frac{\partial \text{Power}(m)}{\partial m} \right],
\]

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

**Accuracy Ratio**

Whilst 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 areas 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 10 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.

**Accuracy Ratios By Country**

In addition to calculating the performance of the RiskCalc Nordic model across sub-segments across the Nordic region, we also examined the performance of the model in each of the countries. Tables 9 - 12 demonstrate that the RiskCalc Nordic model is powerful not only in each country, but also in all industries and size groups within each country. Furthermore, the significantly superior performance of the RiskCalc Nordic model relative to the modified Z-score benchmark is maintained in each of these segments.\(^{62}\)

<table>
<thead>
<tr>
<th>Sector</th>
<th>RiskCalc Nordic</th>
<th>Z-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>71.0%</td>
<td>60.3%</td>
</tr>
<tr>
<td>Construction</td>
<td>70.9%</td>
<td>65.8%</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>69.4%</td>
<td>67.7%</td>
</tr>
<tr>
<td>Services</td>
<td>67.2%</td>
<td>56.5%</td>
</tr>
<tr>
<td>Trade</td>
<td>74.1%</td>
<td>65.1%</td>
</tr>
<tr>
<td>Small</td>
<td>67.4%</td>
<td>59.9%</td>
</tr>
<tr>
<td>Medium</td>
<td>73.9%</td>
<td>60.6%</td>
</tr>
<tr>
<td>Large</td>
<td>78.1%</td>
<td>60.2%</td>
</tr>
<tr>
<td>1 year before default</td>
<td>73.3%</td>
<td>62.7%</td>
</tr>
<tr>
<td>2 years before default</td>
<td>62.7%</td>
<td>51.7%</td>
</tr>
<tr>
<td>3 years before default</td>
<td>57.0%</td>
<td>45.3%</td>
</tr>
</tbody>
</table>

\(^{62}\) Whilst the performance of the modified Z-score is quite close in the manufacturing sector in Denmark and Finland it is worth noting that these figures are based on a number of random samples of the overall data set, and that in 90-95% of samples this pattern of superior performance was maintained.
Due to the relatively small size of the Finnish economy and the time period covered by our data set, we had a limited number of financial statements available for defaulted companies. We therefore decided to include all of these statements in the development sample, and to measure the performance of the RiskCalc™ Nordic model in Finland on a data set consisting of defaulted firms used in development and non-defaulted firms which had not been used in development. Our experience from previous development work, demonstrated in Table 13, is that accuracy ratios based on this approach are similar to those for a full hold-out sample.

<table>
<thead>
<tr>
<th>Sector</th>
<th>RiskCalc Nordic</th>
<th>Z-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>75.1%</td>
<td>65.7%</td>
</tr>
<tr>
<td>Construction</td>
<td>63.8%</td>
<td>55.3%</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>78.9%</td>
<td>75.7%</td>
</tr>
<tr>
<td>Services</td>
<td>77.9%</td>
<td>64.1%</td>
</tr>
<tr>
<td>Trade</td>
<td>76.3%</td>
<td>66.9%</td>
</tr>
<tr>
<td>Small</td>
<td>70.4%</td>
<td>63.9%</td>
</tr>
<tr>
<td>Medium</td>
<td>76.7%</td>
<td>68.4%</td>
</tr>
<tr>
<td>Large</td>
<td>86.1%</td>
<td>70.6%</td>
</tr>
<tr>
<td>1 year before default</td>
<td>76.4%</td>
<td>68.2%</td>
</tr>
<tr>
<td>2 years before default</td>
<td>70.0%</td>
<td>60.9%</td>
</tr>
<tr>
<td>3 years before default</td>
<td>59.9%</td>
<td>52.2%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sector</th>
<th>RiskCalc Nordic</th>
<th>Z-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>75.8%</td>
<td>64.9%</td>
</tr>
<tr>
<td>Construction</td>
<td>80.1%</td>
<td>73.1%</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>75.1%</td>
<td>69.7%</td>
</tr>
<tr>
<td>Services</td>
<td>70.3%</td>
<td>58.2%</td>
</tr>
<tr>
<td>Trade</td>
<td>76.4%</td>
<td>67.0%</td>
</tr>
<tr>
<td>Small</td>
<td>75.3%</td>
<td>65.3%</td>
</tr>
<tr>
<td>Medium</td>
<td>76.0%</td>
<td>65.1%</td>
</tr>
<tr>
<td>Large</td>
<td>71.8%</td>
<td>52.4%</td>
</tr>
<tr>
<td>1 year before default</td>
<td>76.7%</td>
<td>65.7%</td>
</tr>
<tr>
<td>2 years before default</td>
<td>66.5%</td>
<td>52.6%</td>
</tr>
<tr>
<td>3 years before default</td>
<td>57.0%</td>
<td>42.4%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sector</th>
<th>RiskCalc Nordic</th>
<th>Z-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>60.3%</td>
<td>43.2%</td>
</tr>
<tr>
<td>Construction</td>
<td>64.9%</td>
<td>52.2%</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>62.0%</td>
<td>48.5%</td>
</tr>
<tr>
<td>Services</td>
<td>59.0%</td>
<td>48.3%</td>
</tr>
<tr>
<td>Trade</td>
<td>57.7%</td>
<td>39.3%</td>
</tr>
<tr>
<td>Small</td>
<td>60.5%</td>
<td>41.2%</td>
</tr>
<tr>
<td>Medium</td>
<td>60.5%</td>
<td>46.6%</td>
</tr>
<tr>
<td>Large</td>
<td>58.0%</td>
<td>54.1%</td>
</tr>
<tr>
<td>1 year before default</td>
<td>63.5%</td>
<td>45.2%</td>
</tr>
<tr>
<td>2 years before default</td>
<td>51.0%</td>
<td>37.4%</td>
</tr>
<tr>
<td>3 years before default</td>
<td>39.0%</td>
<td>27.5%</td>
</tr>
</tbody>
</table>

Due to the relatively small size of the Finnish economy, and the time period covered by our data set, we had a limited number of financial statements available for defaulted companies. We therefore decided to include all of these statements in the development sample, and to measure the performance of the RiskCalc™ Nordic model in Finland on a data set consisting of defaulted firms used in development and non-defaulted firms which had not been used in development. Our experience from previous development work, demonstrated in Table 13, is that accuracy ratios based on this approach are similar to those for a full hold-out sample.
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 that 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 the occurrence of an expectation of credit loss and the reported date of insolvency. To account for this lag between default and insolvency, we allowed a minimum 6-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 18 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 in Norway for example, for each defaulting firm, we selected the most recent statement between 18 and 41 months prior to the insolvency date and calculated its score. Where no statement was available in this 18 to 41 month period, we excluded the observation. For example, if a firm had defaulted on October 1\textsuperscript{st} 1999, we would have excluded any statements which closed in the previous 18 months, i.e. after March 1998. We would then have used the most recent statement from the period between March 1998 and April 1996, 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”, and a default rate was calculated for each bin. This is the observed calibration “curve” (the bars in Figure 19), which is then smoothed to overcome data anomalies and relate a score to a default rate (the curve in Figure 19). 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.

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. 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.

---

63. 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.
64. These bins can be defined either so as to ensure that they contain the same number of statements, or so that the score “cut-offs” are evenly spaced (although this can lead to some bins containing very few points).
65. 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.
66. 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.
67. Again we allowed a 6 month lag between our default event and the date 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.
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, and we were in a position to do this for Norway and Sweden. Unfortunately, we were unable to do this when calibrating the RiskCalc Nordic model for the Denmark and Finland, but instead have made use of analysis of the drop in power of the model as one moves from a 1 year prediction horizon to more distant prediction horizons. These results, based on 1 to 4 year cohorts calculated using our data sets, were compared with our experience in developing other RiskCalc models (where we had a number of 5-year cohorts available) as well as the changes observed in Norway and Sweden. This analysis allowed us to select a calibration curve with an appropriate slope.

68. 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

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

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 from 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 alphanumerical 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.

Whilst 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 and 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 loss69, 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.

69. 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.